MICROFOUNDATIONS OF FIRM PERFORMANCE: THREE ESSAYS EXAMINING HOW HUMAN CAPITAL AFFECTS FIRM PERFORMANCE ACROSS STRATEGY AND ENTREPRENEURSHIP

by

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ABSTRACT

This dissertation examines how an individual's collection of knowledge, skills, and abilities impacts the performance of firms. I look across two contexts, professional sports and mobile application developers, to investigate several aspects of this relationship. I first examine the mobility of star performers in professional sports and how these individuals impact their new colleagues, leading to increases in firm performance. I then examine how the portfolio of human capital investments for mobile app developers help them improve the performance of their latest application. Finally, I examine how experienced and novice entrepreneurs' actions impact the performance of their latest mobile applications.

This dissertation is dedicated to my wife, Helen, my parents, Martha and Harry, and my brother, Josh.

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CHAPTER 1

INTRODUCTION

Management researchers are becoming increasingly interested in the role that individuals play in the performance of organizations. This dissertation examines several different aspects of the relationship between individuals and organizations, across two distinct contexts. The first paper examines the mobility of star employees in the National Football League. The second and third paper examine mobile application developers, and how their prior experience impacts the performance of their applications.

The first study examines the strategy of hiring stars to improve organizational performance. Prior research finds that when stars are hired, they tend to perform at a lower level than in their previous firm. The effects of hiring stars on firm performance are less clear, but the implication of these studies is that firm performance may suffer when stars are hired from other organizations. Such studies, however, tend to overlook the possibility that a star's abilities can spill over and affect their new colleagues. This paper examines the effects of star mobility in the National Football League. We assess how star mobility affects individual performance, performance of new colleagues, and the performance of the teams that stars join. We find that changing teams reduces the chances of a star performing at the same level as with his previous team, but that his new team actually performs at a higher level.

The second study examines how prior experience and human capital investments shape entrepreneurial outcomes. Previously, researchers have implicitly assumed that investments in human capital are independent, where investments in one type of human capital have no impact on the outcomes of other types of investments. This research argues and find supports for the notion that the performance implications of an entrepreneur's human capital investments are dependent on the levels of other types of investments. Specifically, we find that higher levels of education make industry-specific task experience more valuable, but it makes prior start-up experience less valuable. Prior managerial experience has the opposite effect. Finally, we find that higher levels of education make managerial experience more valuable, and more prior industry-specific task experience make prior start-up experience less valuable. We test our hypotheses in a unique dataset of mobile application developers.

The third study examines the notion in conventional entrepreneurship theory that suggests that individuals with more prior entrepreneurial experience are better able to succeed in their current ventures. Early empirical studies found evidence of this relationship, but more recent empirical studies have begun to call this into question by examining how entrepreneurial experience shapes performance for different types of opportunities. One potential missing link that could help explain this disparity is the impact that an entrepreneur's prior entrepreneurial experience has on the effectiveness of their actions taken to exploit both low and highly novel opportunities. This paper argues that since those with more entrepreneurial experience have developed different thinking patterns than novice entrepreneurs, environmental scanning and prototype testing will have different impacts on performance for novice and experience entrepreneurs. Further, we argue that this will vary if the entrepreneur is exploiting a less novel, more imitative opportunity, or a more novel, more innovative opportunity. We find support for this argument in a unique dataset of mobile application developers.

CHAPTER 2

CATCHING A FALLING STAR: STAR HUMAN CAPITAL MOBILITY AND THE PERFORMANCE OF NFL TEAMS

Introduction

Does adding a talented individual –a star performer– actually improve an organization's performance and create value for the organization? Conventional wisdom maintains that increasing talent in an organization brings performance benefits (Chambers, Foulon, Hanfield-Jones, Hankin, & Michaels III, 1998). Prevailing research, however, casts serious doubt on this common assumption. Several studies observe a decline in star performance after an organizational change. Research on cardiac surgeons (Huckman & Pisano, 2006), star financial analysts (Groysberg & Lee, 2008, 2009; Groysberg, Lee, & Nanda, 2008), and professional basketball players (Berman, Down, & Hill, 2002) shows that hiring talented individuals does not lead to the expected performance at both the individual and organizational levels. One study finds that, despite having higher levels of observable skills (education and experience), individuals hired into a firm performed worse than those who were internally promoted (Bidwell, 2011). Several scholars argue that for firms to achieve a benefit from hiring externally, they must first overcome the adjustment costs associated with the new employees, and therefore performance gains will take time (Hatch & Dyer, 2004; Hitt, Bierman, Shimizu, & Kochhar, 2001). Further, due to their high visibility and general skills, star performers may appropriate their full market value when they change organizations (Coff, 1997; Groysberg & Lee, 2008, 2009; Groysberg et al., 2008). Overall, the prevailing view in this research is that star performers are unlikely to be the predictable source of performance suggested by the conventional wisdom of practitioners (Chambers et al., 1998; Groysberg & Lee, 2008, 2009; Groysberg et al., 2008).

Implicitly, at least, the mechanism by which stars influence organizational performance is through their individual contributions to the new organization. The frequent failure of stars to replicate their performance after moving to a new firm is generally attributed to the loss of firm-specific human capital. To a large extent, these arguments are rooted in beliefs about the importance of firm-specific human capital. This firm-specific reasoning argues that improving organizational performance is achieved through having talented people that invest in organization-specific skills that create value and are appropriable by the organization in which they are employed (Berman et al., 2002). This firm-specific rationale, however, overlooks other potential contributions from highly talented individuals. Several recent studies have shown that star performers have an effect on their colleagues – a spillover of knowledge, skills, and abilities (Azoulay, Graff Zivin, & Wang, 2010; Lacetera, Cockburn, & Henderson, 2004; Oettl, 2012). These studies suggest that star performers could bring more than their individual talent to an organization, but they do not examine the organizational performance implications that may result from any possible spillover effect of star performers.

This study examines one possible way in which a star performer can improve performance and increase value for their hiring organization that is not based on their direct individual performance. Through a star spillover effect, we argue that the organization can improve performance by adding star performers. In essence, by adding a star, the organization allows their current employees the chance to increase their individual performance and productivity. We argue that this spillover effect will outweigh any negative performance effect due to the star performer's loss of previous firm-specific skills, which, studies show, tends to decrease the individual performance of recently hired stars (Groysberg & Lee, 2008, 2009; Groysberg et al., 2008).

This study uses a sports context to examine our hypotheses by examining the effect of hiring star players on organizational performance in the National Football League (NFL). Football players are seen as having easily transferrable, industry-specific skills (Castanias & Helfat, 1991, 2001; Holcomb, Holmes Jr., & Connelly, 2009). Hiring them away from competitors should increase the organization's stock of skills and therefore increase the hiring organization's performance (Crook, Todd, Combs, Woehr, & Ketchen Jr., 2011). However, these stars often possess a nontrivial amount of organization-specific skills, which require time to develop in a new organization. Different teams have their own specific nomenclature, routines, precise patterns of coordination, and require mutual adjustment between players for many different situations. All of these examples of firm-specific knowledge require some time to acquire. Thus, mobility may reduce the chance for organizational improvement soon after personnel changes and would lead to competitive advantage only after new organization-specific, tacit skills were gained (Berman et al., 2002). Using a sample of mobility events in the NFL, we show that, consistent with our argument, while a star's performance tends to suffer after changing teams, this lower performance does not translate to lower performance for the new team. Indeed, we show that gaining stars has the immediate effect of improving organizational performance. We argue that stars are contributing more to the firm than their own unique abilities, and are actually improving the performance of their colleagues (Lacetera et al., 2004; Oettl, 2012) which leads to the organization's increase in performance.

Star Human Capital

Human capital is the knowledge, skills, and ability that an individual possesses (Becker, 1962, 1993). Stars are extraordinarily highly talented individuals whose skills distinguish them from the average worker. Talent can be defined as "any innate capacity that enables an individual to display exceptionally high performance in a domain that requires special skills and training" (Simontin, 1999, p. 436). Highly talented star performers are much more productive than average performers (Lotka, 1926; Narin & Breitzman, 1995). Rosen concludes that "lesser talent is often a poor substitute for greater talent" (Rosen, 1981, p. 846). Zuckerman's (1967) study of Nobel Laureates shows that these stars are not only rarer than the average scientist, but also more productive throughout their careers. She found that American Nobel Laureates, across all disciplines, published earlier, longer, and at a higher rate than the average scientist (Zuckerman, 1967). Prior research also shows that this pattern holds outside of academia. A study of several semiconductor firms found that research productivity, measured as patents, was skewed towards a few top researchers in each organization (Narin & Breitzman, 1995). Further research also shows that the technical inventions of 43 German firms were highly concentrated in a select few individuals within the firms, and that these employees are more tied to their firms' competitiveness (Ernst, Leptien, &

Vitt, 2000). These studies confirm Lotka's (1926) results where he found that a small number of scientists produced a dramatically disproportionate amount of output.

Studies of stars have examined many different industries and professions, including: professional sports (Berman et al., 2002; Ethiraj & Garg, 2012), financial analysts (Groysberg & Lee, 2008, 2009; Groysberg et al., 2008), cardiac surgeons (Huckman & Pisano, 2006), and scientists (Lacetera et al., 2004). All of these studies involve professions where the professionals are seen as employing general skills. Since these skills are general, they are assumed to be both valuable and transferable across organizational contexts (Becker, 1993). Stars in these professions are also highly visible. The combination of high performance and visibility leads them to be competitors to seek after such stars (Lazear, 1986), creating highly competitive labor markets for these professionals (Becker, 1993; Coff, 1997). Such competitive markets can "deplete rivals' human capital pools by "cherry-picking" employees with strong performance" (Gardner, 2005, p. 237).

Transferability of Star Human Capital

While star performers may be in demand by competing firms, views differ as to the postmobility prospects of stars who change organizations. These different views are rooted in beliefs about the transferability of individual skills. Early theory on human capital assumed that if an individual's skills were general, the individuals could utilize such skills in any organization (Becker, 1962, 1993). General skills that were derived from education and training are valuable to many organizations (Becker, 1993). More recent work has questioned this assumption, by arguing that even individuals with highly general skills possess an organization-specific component (Berman et al., 2002; Groysberg & Lee, 2008, 2009; Groysberg et al., 2008; Huckman & Pisano, 2006). This firm-specific component is much more valuable in the organization in which it was created. Therefore, individual skills, even if thought to be general, are less transferable across organizational contexts than early theory supposed. Essentially, the argument is that most star professionals inevitably develop a nontrivial amount of firm-specific human capital. By definition, this firm-specific human capital does not transfer with stars when they switch firms. It follows then, that if performance is a function of general and firm-specific human capital, it will decline when stars switch firms.

Several lines of research suggest that stars can maintain their performance after a mobility event. First, evidence of strong past performance acts as a signal of both future performance and actual, underlying talent (Groysberg & Lee, 2008; Spence, 1973). Second, research in sociology suggests those who become stars are more likely to remain stars. This is termed the Matthew Effect – those with higher status get more recognition for their contributions than those without star status (Merton, 1968). This research indicates that even if a star and a nonstar perform the same, others will perceive the star as having higher performance. Furthermore, the star will be more likely to gain easier access to high quality resources, making it easier to retain star status. Consistent with this reasoning, Groysberg and Lee's (2008) research on Wall Street analysts found that being ranked in *Institutional Investor* in the past was a strong predictor of being ranked in future years. As noted above, stars with high levels of general skills should be valuable to multiple organizations. Therefore, it follows that if stars can maintain their prior performance, and their skills are mostly general, then they should be able to maintain performance when they change organizations. Therefore, we hypothesize:

- H1a*: Individual performance of a star performer will not be affected by changing organizations*.

Recent empirical research, however, challenges the view that stars are not affected by changing organization. In a series of studies, Groysberg and colleagues (Groysberg & Lee, 2008, 2009; Groysberg et al., 2008) studied the effects of mobility on Wall Street financial analysts. They reported that mobility has a strong, negative impact on individual performance, measured as remaining ranked in *Institutional Investor* after changing firms. Huckman and Pisano's (2006) study of mobility and performance among cardiac surgeons reported similar results. A surgeon's performance generally does not seem to transfer to other hospitals (Huckman & Pisano, 2006). While not examining stars, Bidwell (2011) showed that external hires for investment banking firms commanded significant pay premiums suggesting strong prior performance. However, these external hires had significantly lower performance than internal hires and higher rates of involuntary exit.

The general explanation for postmobility performance decline for stars is that there is a strong firm-specific component that contributes to their superior performance (Becker, 1962, 1993). Even in cases that, at least seemingly, have a high level of general human capital, a lack of requisite firm-specific knowledge may limit an individual's ability to transfer skills to another firm (Groysberg et al., 2008). This firm-specific component leads to adjustment costs while the newly hired star develops tacit, organizational knowledge (Hatch & Dyer, 2004; Hitt et al., 2001). Therefore, we would expect to see individuals taking time to develop skills in their new firm, leading to a decrease in performance. This leads to the following competing hypothesis:

- H1b*: Individual performance of a star performer will be negatively related to that individual changing organizations*.

Star Human Capital and Colleague Performance

Whether or not a star's individual performance is transferrable to their new organization, there is a second mechanism through which stars can improve organizational performance. This mechanism is through a spillover effect – the star's ability to improve the performance of their colleagues. Such a spillover increases the ability of colleagues, and therefore increases the level of human capital within the organization. Acemoglu argues "human capital externalities arise when the investment of an individual in his skills creates benefits in other agents in the economy" (1996, p. 779). Others (Glaeser & Mare, 1994; Lucas, 1988; Romer, 1990) argue that increases in the average level of human capital can lead to greater increases for an individual's human capital accumulation. However, these studies focused on city or economy-wide growth, and not what happens in individual organizations.

Other research studying star performers suggests that these individual do provide more than their individual skills. There are at least three potential mechanisms by which stars can affect their new colleagues. First there is the potential for a spillover of the star's knowledge to their new colleagues. Nobel laureates tend to collaborate more with other Nobel winners and future Nobel winners, suggesting that there is a spillover of knowledge that increases the productivity of the Nobel Laureate's younger colleagues

(Zuckerman, 1967). Azoulay and colleagues (2010) found that when a star scientist dies, their former collaborators suffer a long-term degradation of their quality-adjusted publications. They argue "these effects appear to be driven, at least in part, by the existence of knowledge spillovers across members of the research team" (Azoulay et al., 2010, p. 580). A second mechanism is through peer effects – the star can actually help change the behavior of their new colleagues, legitimizing certain practices that can potentially increase performance. Lacetera, Cockburn, and Henderson (2004) found that firms hiring a star scientist in the pharmaceutical industry led to a change in the behavior of currently employed scientists. This change led to more science-driven drug discovery capabilities, even in research areas distinct from the star's focus. A study of star Wall Street analysts' performance shows that individual performance increases when high quality colleagues surround them (Groysberg & Lee, 2008). In a reconceptualization of star human capital, Oettl (2012) makes a compelling argument that the impact of stars is not limited to their individual performance and that examining the impact of stars should include the effect they have on colleagues. In his framework, not all stars are the same. Some are focused on their individual performance but a second type of star is likely to help colleagues. When those in the latter category died, the output quality of their former colleagues declined (Oettl, 2012). Finally, a third mechanism by which stars can improve their colleagues' performance is through complementarities. A recent finding in research on the National Basketball Association found that, contrary to the researchers' expectations, NBA stars were positively associated with team complementarity (Ethiraj & Garg, 2012). Other research suggests that performance spillovers are much more likely to be created by stars than nonstars. Campbell, Saxton, and Banerjee (2013) found no evidence of a human capital spillover effect for NBA players. This research suggests that the spillover that is obtained by hiring a star is not obtainable when lower-quality individuals are hired.

The above arguments lead us to the conclusion that a star performer can contribute more to an organization than their individual skills, and can affect the performance of their new colleagues. Therefore, we hypothesize:

- H2*: Adding star performers will be positively related to an increase in colleague performance in the hiring organization*.

Hiring Star Human Capital and Organizational Performance

As noted above, several studies show that stars who change firms have difficulty in maintaining star-level performance (Groysberg & Lee, 2008, 2009; Groysberg et al., 2008). This finding is at tension with the general premise that an organization's human capital is positively associated with organizational performance (Crook et al., 2011). In a meta-analysis of 66 studies, Crook and his colleagues found that "human capital is strongly related to performance" (Crook et al., 2011, p. 451). They suggested that for firms to improve their performance they should hire the most talented human capital and work to retain their services (Crook et al., 2011). The human capital effect on performance has been shown in a variety of firms. Ericksen's (2012) longitudinal study of Danish manufacturing firms reported on how changes in human capital related to changes in firm performance. He found that an increase in the level of human capital of employees or of management raised firm performance (Eriksen, 2012). Several studies have also shown that stars play a significant role in movie box performance (Elberse, 2007; Ravid, 1999).

In general, when firms add stars, it should increase human capital (assuming they do not have offsetting losses of human capital via exits of other key employees). And, ceteris paribus, increasing human capital should result in improved performance. The above argument assumes two important conditions, which will not always hold. First, a star's talent must not consist primarily of human capital that is highly specific to another firm, and that firm-specific capital is not transferable to the new firm (Becker, 1993). Second, the argument assumes that the star will not appropriate all of the value derived from performance gains in the new firm (Coff, 1999). However, nonfinancial aspects of performance are not generally subject to appropriation. For the purposes of this study, we follow Powell (2003) and examine wins. Setting aside the above boundary conditions, how does a star influence performance in a new firm? The first mechanism is that a star's individual performance is transferable, and therefore increases the organization's performance through their individual performance. This occurs when the star's skill portfolio is very general (Campbell, Coff, & Kryscynski, 2012). A second way that a star may improve firm performance is by affecting the performance of their colleagues through either their helpfulness (Oettl, 2012), through motivating/stimulating their colleagues to perform better (Allison & Long, 1990; Zuckerman, 1967), through increasing team complementarity (Ethiraj & Garg, 2012), or through attracting other talented colleagues to the firm. Yet, another way that stars may influence performance is through signaling firm credibility or legitimacy to various stakeholders such as customers, potential employees, investors, and others (Connelly, Certo, Ireland, & Reutzel, 2011; Spence, 1974). Therefore, we hypothesize:

- H3*: Adding star performers is positively associated with an increase in performance for the hiring organization*.

Empirical Context

This paper examines the movement of star National Football League (NFL) players. Football is a competitive team sport, with individual players on different teams performing similar, interdependent tasks (Holcomb et al., 2009). The NFL was founded in 1920[1] and has become the most watched sport in the U.S.,[2] increasing the visibility of both the teams and of individual players. There are numerous websites, televisions programs, and even a television network dedicated to the NFL, further increasing player visibility. Currently there are 32 teams in the NFL, with over 1600 players on active rosters.[3]

The NFL is an interesting arena in which to examine human capital mobility. Data is abundantly available. The data was obtained from several online resources, including the official NFL website, www.nfl.com, and www.pro-football-reference.com. The later website consists of historical documentation of NFL players, teams, seasons, and statistics going back to the inception of the sport. Due to differences in the sport, we have included only those years in the Super Bowl era, which equates to every year since 1966. We stop our data collection in 2011. According to the NFL league office, the average player's career is six years for players who make an opening day roster. Given

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[1] http://static.nfl.com/static/content/public/image/history/pdfs/History/Chronology_2011.pdf

[2] According to http://www.sportsmediawatch.com/2012/07/halftime-the-50-most-viewed-sporting-events-of-2012-so-far/, 12 of the top 50 most watched sporting events in the U.S. in 2012 were NFL games, with over 111 million viewers for the Super Bowl alone.

[3] www.nfl.com

this figure, the length of time each team has been in the league, and the fact that each team has a 53-man roster, over 11,000 men have played in the NFL since 1966.[4] The NCAA estimates that only .08% of all high school football players even make it onto an NFL roster.[5] Therefore, playing in the NFL at all requires a high level of skill and ability.

Measures

Star measure. For our research, we followed other star human capital literature and utilized a subjective measure of star (Groysberg & Lee, 2008, 2009; Groysberg et al., 2008) rather than an objective measure. We defined a star player as a player who had played in three NFL Pro-Bowls. The Pro-Bowl is the NFL's version of an All-Star game, where the best players in the league that year come together to play an exhibition game. We chose Pro-Bowls as our star measure because it is one of the most salient measures of pro football performance. Players are selected to the Pro-Bowl by a combination of fans' votes, coaches' votes, and votes from other players.[6] While many fans vote for their favorite players, coaches and players generally know who is playing the best in a given season. Furthermore, it is difficult to objectively determine and compare the performance of players across positions. For example, it would be very difficult to objectively compare the performance of defensive tackles versus quarterbacks. Using Pro-Bowl appearances alleviates this difficulty. Finally, many player contracts also include incentives for making the Pro-Bowl,[7] making it a goal that many players strive to

[4] This figure probably underestimates the actual number of players. Reasons for this include injuries, suspensions, and practice squad players (who do not dress and play in games) who are professional football players and yet not included in this rough estimate.

[5] http://www.ncaa.org/wps/wcm/connect/public/ncaa/pdfs/2011/2011+probability+of+going+pro

[6] www.nfl.com/probowl

[7] http://sports.yahoo.com/blogs/nfl-shutdown-corner/champ-bailey-julius-peppers-top-list-nfl-pro-163029343--nfl.html

achieve. To overcome any possibility that an individual had only one strong season, we required a star player to make three separate Pro-Bowls. This ensured that we were truly capturing star performance, and not an individual who had one strong season and who was unable to repeat their strong performance.

For every player with at least three Pro-Bowl selections, we then examined all players who changed teams after playing in the third Pro-Bowl versus those who did not move. Changing teams did not have to be immediately after playing in the third Pro-Bowl. Some players played one or more seasons in between the third Pro-Bowl and a move. Additionally, some players played in additional Pro-Bowls between their third Pro-Bowl selection and a move. Overall, there were 610 players who played in three Pro-Bowls. Of those, 334 players changed teams after playing in their third Pro-Bowl prior to the 2011 season.

Dependent variables. For the player-level individual analysis, the dependent variable is a dichotomous variable that indicates whether or not the player played in a Pro-Bowl in a given season after being classified a star (e.g., after playing in three Pro-Bowls). The data for each player starts the year after the player makes their third Pro-Bowl – they become classified a star – and runs through the end of their career or 2011, whichever comes first.

To test for the spillover effect, it was necessary to construct a measure of colleague performance. Since it is very difficult to compare performance across different positions in the NFL, we also utilized the Pro-Bowl for this dependent variable. We calculated the number of Pro-Bowl selections for a given team at the end of the season. We then subtracted the number of added stars, if any, who made the Pro-Bowl in the year that they moved. This measure gives an indication of how the star's mobility affects the individual performance of their colleagues.

For the team-level models, the dependent variable is change in wins. This is calculated as wins in the current season minus wins in the previous season. This was chosen as the dependent variable because it directly shows the improvement of the team from one season to the next. Using wins as the dependent variable showed no substantive differences in the results. Powell (2003) modeled firm financial performance (industry leadership in profits) as 'wins' and found that the performance distributions closely matched what was found in other areas, including sports. Therefore, our dependent variable, change in wins in sports, is consistent with other business performance measures.

Independent variables. For the individual player-level results we are interested in determining how individual mobility affects the probability of remaining a star player. Therefore, our key independent variable was a dichotomous variable that indicates the first time a star changed teamed after playing in their third Pro-Bowl. This was set to '1' in the year of the star player first changed teams after being classified a star.

To analyze the spillover hypotheses, we calculated the total number of stars the team gained in a given year. This was calculated at the team level, and only included firms gaining a star player in the first move they made after becoming classified a star. This independent variable was also used in the organizational performance models. An alternative independent variable, a dummy variable for gaining one or more star performers, showed no substantive difference in results.

Control variables. For the player-level models, several variables were included in the model. First, we controlled for the experience of the player, which was calculated as the total number of years the player had played in the NFL prior to the given season. Since the ability and skills of NFL players deteriorate rapidly (Moir, 2009), this is a key control variable to include. Second, we control for several high-visibility positions: quarterback, running back, and wide receiver. These positions are usually the more highly visible ones in the media, which may lead to more Pro-Bowls from players in these positions. We further controlled for several variables related to team improvement. They are change in wins, change in points scored, and change in points allowed. We also controlled for whether or not the team made the playoffs in the prior year and the number of Pro-Bowlers on the team in the prior year. Since winning (and team improvement) is highly correlated with the number of Pro-Bowlers on a given team, controlling for how much a team improves is essential for separating out star effects. Finally, we had four controls for coach's human capital which could impact the performance of individual stars (Holcomb et al., 2009; Sirmon, Gove, & Hitt, 2008). The controls are coach's tenure with the current team entering the season, whether or not a coaching change occurred before or during the season, the coach's cumulative winning percentage entering the season, and the coach's cumulative playoff winning percentage entering the season.

For the spillover and organizational performance models we also included several control variables. First, we control for the experience of the stars that the team gained. As discussed above, NFL players tend to have rapid deterioration of their athletic skills (Moir, 2009); therefore it is critical that their experience be accounted for in the models. We measured the number of years of NFL experience for each star. Then, for each team, we averaged this measure over the total number of stars gained. For teams that added no stars, this control was set to '0.'

Another key control is the strength of the team, as better teams would have a better chance at improving their performance. To control for the strength of the team, several different control variables were included. First, we included a variable for the total number of stars on the team at the beginning of the season other than those gained, which is expected to increase the team's performance, as it is indicative of higher levels of human capital (Crook et al., 2011). The second was a dummy variable indicating whether a team made the playoffs in the prior year, which is also expected to show a higher quality team. The third was the total number of points scored by the team in the prior season. This variable is expected to decrease performance because the more points a team scores in the previous season would make it harder to improve this season, as there is a cap to the number of wins in a given season (currently 16), and the more points a team scores in a given season, the more likely they are to win more games. Finally, the total number of points allowed by the team in the prior season was included, and expected to increase the team's ability to improve this year. This is due to the fact that as a team gives up more points in the previous year, they have more room to improve in the current year (because an increase in points allowed is associated with winning fewer games in a given year).

Finally, it is important to account for the ability of the coach/manager, as several recent papers (Holcomb et al., 2009; Sirmon et al., 2008) show that coaches have an important impact on their team's performance. Following previous research (Brown, 1982; Holcomb et al., 2009; Pfeffer & Davis-Blake, 1986; Sirmon et al., 2008), we included several variables to capture the human capital of the coach. First, coaching tenure was controlled for as the number of years the head coach had been with the team entering the season. This is expected to increase the number of wins. Also included was a dummy variable indicating if a coaching change occurred either before or during the season, which is expected to reduce the number of wins in that year. We also included measures of the coach's cumulative winning percentage entering the season, and cumulative playoff winning percentage entering the season.

We also included two separate year control variables in the organization-level analysis. In 1978, the NFL changed from a 14 to a 16 game schedule; therefore increasing the number of chances a team has to gain a win (and the increase in wins could be solely because of this increase in chances to win). To control for this change in the number of games played in the NFL, we included a dummy variable *Year1978*. In 1982 and 1987 there were labor issues in the NFL which led to shortened NFL seasons. A dummy variable was included, *Strike Years*, to control for this.

Analysis Techniques

Due to the binary and longitudinal nature of the dependent variable in the player-level model, those results were calculated using a random-effects logistic regression model, with standard bootstrap errors (clustered by player) to control for possible unobserved heterogeneity in the errors (Wooldridge, 2010). A fixed-effects logistic model was inappropriate for this situation because over 30% of the players did not play in another Pro-Bowl. These players would have been dropped from a fixed-effects model. Therefore, a random-effects model is the appropriate choice.

For the spillover model, the dependent variable was the count of the number of nonstar Pro-Bowlers selected at the end of the season. This variable is a count, ranging from 0 to 13. Therefore, we utilized negative binomial, fixed effects regression. Since there could be heterogeneity in the errors across teams, we use bootstrapped standard errors (Wooldridge, 2010). These were chosen because there are no robust errors for longitudinal negative binomial models available in Stata 12. Using bootstrapping allowed us to cluster the errors to account for across-team heterogeneity.

In the organizational performance models, the dependent variable was a change score – the change in wins. Therefore, there was potential for serial correlation in the models. When there is serial correlation, fixed- and random-effects models are biased (Wooldridge, 2010). To control for this bias, we utilized cluster robust standard errors (Huber, 1967; White, 1980), which provide consistent estimates of the standard errors in the face of serial correlation and heteroskedacticity (Wooldridge, 2010). Furthermore, the robust errors also control for across-team heterogeneity. We ran both fixed and random-effects models, and tested for consistency using the Hausman test. Since the Hausman test showed a significant difference between the models ($\chi^2 = 23.43$, $p = 0.0243$), we present the fixed-effects models (the random-effects are available upon request). Further, we ran additional models using generalized estimating equations and random-effects generalized least squares methods. Results were substantially the same across all models; therefore we choose to present the fixed effects models for ease of interpretation. All models were run in Stata 12. All models were checked for multicollinearity using ordinary-least squared (OLS) regressions and variance inflation factors (VIFs). Results showed that multicollinearity was not an issue for this data.

Results

Tables 2.1 and 2.2 show the summary statistics for the individual and the organization (including the spillover) level models, respectively. There were largely no unexpected results in the correlations between variables. For the individual players, both mobility and experience were negatively correlated with playing in the Pro-Bowl, as expected. In the team level models, stars gained was positively associated with change in wins, while stars lost was negatively associated with change in wins, in line with our hypotheses.

Table 2.3 presents the results for the individual-level hypotheses (1a and 1b). We found support for hypothesis 1b but not hypothesis 1a. Model 1a is the control model. The controls acted largely as expected. Model 1b is the full model, including effects of mobility and the experience of the individual player. For each further year of experience, ceteris paribus, a NFL star has a decrease in the log-odds of playing in the Pro-Bowl of -.37. Controlling for experience, results show that the first move of an NFL star reduces the log-odds of playing in a Pro-Bowl by -.88. This supports hypothesis 1b, that mobility hurts individual performance, while showing no support for hypothesis 1a, that a star's individual performance was transferable and did not diminish when they changed organizations.

Table 2.4 presents our tests of the spillover prediction, which is Hypothesis 2. Our results show support for this hypothesis. Model 2a is the control model. Model 2b presents the addition of stars with all control variables included. Results show that each star added is associated with a .09 (p=.046) increase in the log-count of other Pro-Bowlers. Experience of the star was not significant. This supports Hypothesis 2.

Table 2.5 presents the results for the organizational performance hypothesis. We found that adding a star player improves firm performance in the year they were added, regardless of their level of experience. Model 3a is the control model. The control variables act largely as expected. Model 3b adds the variables for gaining stars and the measure of the star's experience. As shown, an increase in stars gained is positively associated with an increase in wins for the team. The experience variable is not significant. Results indicate that each star gained is associated with a 0.69 more wins than in the previous year, all else equal. This provides support for Hypothesis 3.

Robustness Checks

We also ran several robustness checks for our individual-level models. First, we ran the full model examining any star move (versus the first move). Here we found that mobility still negatively impacts a player's individual performance. We also ran fixed-effects models, which dropped all stars that did not play in another Pro-Bowl. This model indicates that even for players who play in another Pro-Bowl, changing teams still has a negative, statistically significant effect, further supporting our results. Finally, we ran two further models, further lagging the independent variable. This examines whether mobility in the prior season impacts a star's individual ability. The results, for both first move and all moves, suggest that a player's individual performance remains lower than if they didn't move two seasons after changing teams. All of these models are available from the authors on request.

We also ran further tests to control for possible nonrandom selection. The assignment of stars to teams is not random, and could reflect the fact that stars are going to teams that have higher levels of talent and are already improving. This could bias our results. We utilized a propensity-score matching methodology to attempt to test if selection bias is present in our models. First, we created a propensity score model using the same control variables we used in the organizational performance models. The dependent variable for this was a dummy variable indicating that a team gained at least one star prior to the given season. Once we calculated the propensity to add a star, we used matching methods on both change in wins and wins, matching on the observable team performance parameters. These results indicate that the treatment effect of the treated (where treatment is gaining at least one star) is positive and largely significant. This suggests that while there might be nonrandom selection, it is not biasing our results. All models are available from the authors on request.

Discussion and Conclusion

Conventional wisdom asserts that adding highly talented individuals to an organization should increase organizational performance (Chambers et al., 1998). Recent empirical work suggests that this is not actually the case (Groysberg & Lee, 2008, 2009; Groysberg et al., 2008). Our research attempted to disentangle these disparate findings by examining the consequences of adding star performers in the NFL. Our results show that when a star player changes teams, he is less likely to play in a Pro-Bowl in that year. However, the team that adds the star does shows an increase in the number of other players on the team making the Pro-Bowl. Furthermore, the team shows a marked improvement, suggesting that stars are adding more to the organization than their individual skills. These results suggest that the star performers are adding more to the organization than their individual contribution to the organization by increasing the ability of their new colleagues.

These results make several contributions to the literature. First, we add to the growing research surrounding star mobility and organizational performance (Groysberg & Lee, 2008, 2009; Groysberg et al., 2008). Groysberg and colleagues show that star human capital has a firm-specific component that leads to less transferability of skills than conventional wisdom might suggest. Our results are consistent with the notion of an organizational-specific component of NFL players' skills. However, we also show that adding these stars actually leads to organizational performance increases not decreases. By positing and finding results consistent with a star spillover effect, we have shown that the firm performance is not solely a function of the individual skills brought by the star performer, but also a function of the increased productivity of the firm's current employees.

We also add to research showing the effect of star performers on their colleagues. We extend the work of Lacetera and colleagues (2004). They showed that adding stars led to a change in behavior of those already working within the firm. However, while they observed a change in behavior they did not test for whether such changes increased organizational performance. Recent research by Azoulay and colleagues (2010) and Oettl (2012) also links star performers to spillovers and colleague performance. Again, these authors did not link the spillover to organizational performance. Consistent with these studies, our results suggest that star performers bring more than their individual skills to an organization, and actually affect the performance of their new colleagues. We showed that adding a star player increases the number of their colleagues who make the

Pro-Bowl. Further supporting this supposition is the fact that the age variable was not significant in the team-level model. If a star added only their individual athletic ability and skills, those skills should decline rapidly with age in this context, and adding an older player should not increase a team's performance. There was no evidence of this being the case in this data. Overall, our results suggest that adding star performers complements the other players that the team currently has by helping them to become better players, even if the stars themselves do not improve in performance.

There are several limitations to this research. First, when studying sports there are questions surrounding the generalizability of the results. Sports, however, do provide a good context for many management studies. It has been argued that "there is sufficient contextual overlap to reasonably expect that knowledge will generalize, regardless of whether the direction is from work (or education, or military, or other organizational context) to sport, or conversely" (Day, Gordon, & Fink, 2012, p. 399). Other researchers also show how sports provides a strong context for organizational researchers (Wolfe et al., 2005). It has also been shown that the distribution of wins in sports is closely related to winning in industry competition (Powell, 2003). In this context, studying the NFL has more generalizability than many other contexts. There are many professions where industry-specific human capital exists in which it is relatively easy for everyone to see who the stars are. Academia is one example, where citation counts and journal publications act as a signal of higher levels of general human capital, much like playing in Pro-Bowls signals a more talented football player. Furthermore, star academics are able to move between universities, and it is expected that their human capital is highly transferable to the new university. In fact, our results should extend to star academic researchers, since they could also improve the performance of their new colleagues (for example, by implementing research meetings, providing feedback on papers, and bringing more attention to the university).

A second limitation is in our measure of performance. Wins and losses are likely just one performance measure of NFL teams. We only examined the improvement in a team's wins, but presumably, most also care about their financial results. Hiring stars could adversely affect a team's bottom line even as the stars help the team win on the field (Coff, 1997, 1999; Ethiraj & Garg, 2012). The case of the NFL is, admittedly, idiosyncratic even for professional sports teams. Salary caps, which fix a ceiling on a team's total payroll, prevent team owners from losing appropriation contests to a team of players collectively. The contest for appropriation is more between players than between players and owners. If a player is able to command an abnormally high salary, owners are not harmed. Instead, a player's teammates will collectively have to make less in order for the team to stay under its salary cap.

Perhaps the most important managerial implication of our findings is that a narrow focus on a star's postmobility individual performance may lead observers to overlook organizational benefits that accrue to the organization. These benefits occur because of the spillovers from the star to their new colleagues. We posited three potential mechanisms that can account for this. First, we argued that stars can spill over knowledge to their new colleagues. Second, stars can actually affect the behavior of their new colleagues creating a peer effect that can improve their performance. Finally, stars can increase team complementarity. Managers who fail to take these spillovers into account could potentially miss a key way to improve the performance of their firm.

There are several future lines of research opened up by this research. One possible research area would be to study possible further outcomes of the star spillover effect. For example, to what extent is the effect of this spillover sustainable for organizational performance? The work by Azoulay et al. (2010) and Oettl (2012) suggests that when the star leaves, the spillover disappears and the star's colleagues performance decreases. However, if the star's colleagues are truly building human capital, then these skills should remain after the star has left. Further, it would be interesting to understand the ability of the star's new colleagues to appropriate the value that they are creating with the star. Another interesting extension would be to further explore how the stars interact with the team's complementary resources. Is it better for a team to add to its weakness, as suggested by the corporate acquisitions literature, or to build on its strengths? In other words, should a team with a strong offense focus on bringing in more offensive stars to complement what they already have, or should they bring in defensive stars to strengthen a weaker unit? Exploring this could give managers ideas on how to tailor their human capital strategy to better complement their firm's current human capital.

Overall, this research shows that adding stars can improve an organization's performance, even in a situation where there are moderate levels of team coordination needed. This is despite the fact that the individual star does not, on average, perform as well with their new team. The results suggest that by adding a star, an organization can improve the performance of their other employees. This research suggests that it is better to keep your current stars and add new ones to improve your organization's performance.

Table 2.1

Summary Statistics for Player Level Data

Variables	*N*	mean	*sd*	min	max
Pro-Bowls	3377	0.35	0.48	0	1
First Move	3377	0.10	0.30	0	1
NFL Experience	3377	8.97	3.05	3	24
QB	3377	0.08	0.27	0	1
RB	3377	0.09	0.29	0	1
WR	3377	0.12	0.33	0	1
Win Differential	3373	-0.20	3.23	-10	10
Lagged Playoffs	3373	0.50	0.50	0	1
Lag Pro-Bowlers	3373	4.13	2.58	0	13
Change in Points Scored	3373	-2.31	75.53	-243	351
Change in Points Allowed	3373	5.43	73.77	-241	270
Coach's Tenure	3377	4.39	4.83	0	28
Coaching Change	3377	0.20	0.40	0	1
Coach's Win Percentage	3377	49.50	22.41	0	175
Coach's Playoff Win Percentage	3377	33.07	29.55	0	100

Table 2.2

Summary Statistics for Team Level Data

Variables	*N*	mean	*sd*	min	max
Win Differential	1290	0.06	3.30	-10	10
Nonstar Pro Bowlers	1322	3.13	2.49	0	13
Stars Gained	1322	0.25	0.55	0	5
Average Experience Gained	1322	1.96	4.01	0	19
Stars Not Gained	1322	2.33	1.99	0	11
Lag Playoffs	1290	0.35	0.48	0	1
Lag Points Scored	1290	315.02	72.09	103	589
Lag Points Allowed	1290	313.98	68.25	128	533
Coach's Tenure	1322	3.48	4.11	0	28
Coaching Change	1322	0.25	0.43	0	1
Coach's Win Percentage	1322	44.98	21.84	0	87.5
Coach's Playoff Win Percentage	1322	27.30	29.72	0	100
Year>1978	1322	0.02	0.14	0	1
Strike Years	1322	0.04	0.20	0	1

Table 2.3

Logistic Regression for Star Player Pro-Bowl Appearances

VARIABLES	**Model 1**	**Model 2**
First Move		**-0.965*** **
		[0.197]
NFL Experience		**-0.420*** **
		[0.036]
QB	**-0.151**	**0.356**
	[0.270]	[0.365]
RB	**-0.627** **	**-1.403*** **
	[0.212]	[0.272]
WR	**-0.503* **	**-0.670* **
	[0.215]	[0.279]
Change in Wins	**0.043+**	**0.058* **
	[0.023]	[0.026]
Lag Playoffs	**0.316* **	**0.429** **
	[0.130]	[0.142]
Lag Pro-Bowlers	**0.227*** **	**0.183*** **
	[0.026]	[0.029]
Change in Points Scored	**0.005*** **	**0.005*** **
	[0.001]	[0.001]
Change in Points Allowed	**-0.004*** **	**-0.004*** **
	[0.001]	[0.001]
Coach's Tenure	**-0.016**	**-0.028**
	[0.017]	[0.018]
Coaching Change	**-0.155**	**-0.148**
	[0.138]	[0.159]
Coach's Win %	**0.003**	**0.005**
	[0.003]	[0.003]
Coach's Playoff Win %	**-0.003**	**-0.002**
	[0.003]	[0.003]
Constant	**-1.794*** **	**1.886*** **
	[0.216]	[0.354]
Log Likelihood	-1932.414	-1698.643
Observations	3,373	3,373

Bootstrapped (1000 Reps) Standard errors in brackets
**** p<0.001, ** p<0.01, * p<0.05, + p<0.1*

Table 2.4

Negative Binomial Fixed Effect Regression for Number of Pro-Bowlers

VARIABLES	Model 1	Model 2
Stars Gained		**0.089***
		[0.045]
Average Experience Gained		**-0.003**
		[0.005]
Stars Not Gained	**0.038****	**0.037****
	[0.012]	[0.012]
Lag Playoffs	**0.161****	**0.162****
	[0.055]	[0.055]
Lag Points Scored	**0.002*****	**0.002*****
	[0.000]	[0.000]
Lag Points Allowed	**-0.002*****	**-0.002*****
	[0.000]	[0.000]
Coach's Tenure	**-0.015***	**-0.014***
	[0.006]	[0.006]
Coaching Change	**-0.177*****	**-0.178*****
	[0.045]	[0.045]
Coach's Win %	**0.001**	**0.001**
	[0.002]	[0.002]
Coach's Playoff Win %	**0**	**0**
	[0.001]	[0.001]
Year>1978	**-0.036**	**-0.048**
	[0.152]	[0.150]
Strike Years	**0.015**	**0.019**
	[0.050]	[0.049]
Constant	**1.803*****	**1.804*****
	[0.236]	[0.235]
Observations	1,290	1,290
Log Likelihood	-2,507.22	-2,504.87

Bootstrapped (500 replications)
Standard errors in brackets
**** p<0.001, ** p<0.01, * p<0.05, + p<0.1*

Table 2.5

Fixed Effects Regression for Change in Team Wins

VARIABLES	*Model 1*	*Model 2*
Stars Gained		**0.692***
		[0.253]
Average Experience Gained		**-0.035**
		[0.031]
Stars Not Gained	**0.125***	**0.118***
	[0.049]	[0.049]
Lag Playoffs	**-1.062*****	**-1.055*****
	[0.226]	[0.231]
Lag Points Scored	**-0.015*****	**-0.015*****
	[0.001]	[0.001]
Lag Points Allowed	**0.011*****	**0.011*****
	[0.002]	[0.002]
Coach's Tenure	**-0.044***	**-0.040***
	[0.017]	[0.018]
Coaching Change	**-1.106*****	**-1.106*****
	[0.191]	[0.185]
Coach's Win %	**-0.018*****	**-0.019*****
	[0.004]	[0.004]
Coach's Playoff Win %	**0.013*****	**0.012****
	[0.003]	[0.003]
Year>1978	**0.743**	**0.642**
	[0.483]	[0.472]
Strike Years	**-2.051*****	**-2.052*****
	[0.344]	[0.348]
Constant	**2.429*****	**2.387*****
	[0.469]	[0.471]
Observations	1,290	1,290
R-squared	0.238	0.244

Robust standard errors in brackets

**** p<0.001, ** p<0.01, * p<0.05, + p<0.1*

CHAPTER 3

PORTFOLIO HUMAN CAPITAL: THE INTERDEPENDENCE OF ENTREPRENEURIAL HUMAN CAPITAL INVESTMENTS

Introduction

Researchers are becoming increasingly interested in what role an entrepreneur's human capital and prior experience play in exploitation of entrepreneurial opportunities. Human capital is defined as the knowledge, skills, abilities, and expertise that individuals gain through their investments in education and experience (Becker, 1962, 1993), and therefore is closely related to an individual’s stock of knowledge. Many researchers have examined the role of human capital and experience in the performance of entrepreneurs, and have largely found that human capital investments improve entrepreneurial performance (Bates, 1990; Bosma, van Praag, Thurik, & de Wit, 2004; Bruderl, Preisendorfer, & Ziegler, 1992; Cooper, Gimeno-Gascón, & Woo, 1994; Davidsson & Honig, 2003; Dencker & Gruber, 2015; Eesley & Roberts, 2012; Hmieleski, Carr, & Baron, 2015; Unger, Rauch, Frese, & Rosenbusch, 2011). In their recent meta-analysis, Unger and colleagues (2011) found that specific investments, such as industry and prior start-up experience, are a larger predictor of success than more general investments, such as education.

However, these researchers have implicitly assumed that all human capital investments are independent—that is, the performance effects of one type of investment does not impact the performance implications of another investment. Recent theorizing in strategy has argued that an individual's human capital is actually a portfolio of skills (Campbell, Coff, et al., 2012). This means that some human capital investments could complement one another, meaning that a high level of investment in one type of human capital could increase the value of some other investment. Alternatively, higher levels of one type of human capital investments could reduce the performance implications of another investments. By ignoring the interaction between investments, researchers could be drawing incorrect conclusions about the effectiveness of different types of investments (Unger et al., 2011). These researchers could be under- or over-estimating the importance of general and specific human capital investments.

This research bridges the gap by arguing that the performance implications of an entrepreneur's human capital investments are dependent on each other. We argue that an increase in an individual's investments in general human capital will improve the performance effects of their specific human capital investments. Specifically, we find support for the argument that higher levels of education improve the performance effects of industry-specific task experience and higher levels of managerial experience improve the performance effect of prior start-up experience. Opposite to our predictions, we find that higher levels of education reduce the value of prior start-up experience on current entrepreneurial performance, while higher levels of managerial experience reduce the value of prior industry-specific task experience. We find support for our arguments that investments in education and managerial experience are complements, with high levels of both types of investments leading to higher performance. Finally, we argue and find that high levels of both industry-specific task experience and prior start-up experience harm each other. We find that the increased performance effects of prior task-specific human capital investments actually rise faster for those with less prior start-up experience than for those with high levels of prior start-up experience.

This paper will test these conjectures in a unique survey of Google Play™ app developers. We develop a novel survey instrument that captures a large number of possible human capital investments that will be used to determine how the interactions between different investments impact entrepreneurial performance. This is a strong setting in which to test entrepreneurial human capital hypotheses for several reasons. First, our setting allows us to isolate human capital effects of individual entrepreneur founders versus entrepreneurs working in teams. This removes a possible confounding issue—the human capital of the team substituting for the human capital of the founder (Hmieleski et al., 2015). Second, our setting allows for a unique measure of entrepreneurial performance—app downloads. It has been extremely difficult to measure entrepreneurial performance, especially given that, in the early stages, many firms do not yet have sales and profits, and this setting allows us to objectively measure performance. Finally, we are able to capture many entrepreneurs that other research designs cannot see. Many entrepreneurial studies capture data on young firms, but they have already achieved sales (for example, see: Hmieleski et al., 2015), missing potential entrepreneurs who have already failed. Since we capture our human capital measures before any performance data, we are able to capture entrepreneurs who never achieve any success, limiting our concerns with success bias that plague many entrepreneurial studies.

Literature Review

Human capital research began with Becker's (1962, 1993) pioneering work on the subject. He defined human capital as the knowledge, skills, and abilities that individuals gain through investments in schooling, work experience, on-the-job training, etc. Prior experience, through these investments, builds up competencies and skills that should impact performance of organizations, both large firms (Crook et al., 2011; Hitt et al., 2001) and smaller entrepreneurial firms (Unger et al., 2011). Within the entrepreneurship literature, researchers have directly examined how the entrepreneur's human capital investments and prior experience impact firm performance. Entrepreneurial scholars have largely adopted Becker's (1962, 1993) definition of human capital and argue that investments in human capital lead to skills that the entrepreneur can use while exploiting a new opportunity. These researchers have looked at a number of different types of investments, including general investments (such as education and managerial experience) and specific investments (such as industry and start-up experience).

General human capital investments are largely seen as investments in education or general work experience. Investments in education, general experience, and managerial experience are seen as giving the entrepreneur general knowledge that is useful across a large number of contexts of industries (Becker, 1993). Education can directly improve performance, as investments in education help build general skills, including critical thinking and reasoning skills that are valuable for a variety of contexts (Becker, 1962, 1993). Education can also help the entrepreneur build a diverse knowledge set. These investments can also lead to increased critical thinking and reasoning skills (Eesley & Roberts, 2012). Investments in education are also seen as a signal underlying quality and talent (Spence, 1973). Since it is difficult to observe an individual's level of talent, and only those who will benefit from an investment are likely to make it, it has been argued that only those with higher talent make general investments as they are the most likely to be able to reap the rewards (Becker, 1962, 1993), and therefore those with higher levels of education are likely to be more talented than those with lower levels of education. Investments in managerial experience help individuals understand how to manage resources, manage time, and coordinate with teams (Davidsson & Honig, 2003; Hitt et al., 2001). These skills should also be valuable across a number of contexts.

Empirical studies largely confirm theory that argues increases general human capital improves entrepreneurial performance. Bates (1990) found that individuals with higher levels of education started ventures that were more likely to survive. Chandler and Hanks (1994) found, in a study of manufacturing ventures, that increased managerial competence was linked to the better utilization of resources. Bosma and colleagues (2004), in their study of Dutch entrepreneurs, found that higher levels of education were associated with increased profitability, while general work experience was linked to higher employment growth. Other work has also shown this link. Colombo and Grilli (2005) found that economics, management, and technical education were linked to growth in their study of Italian high-tech start-ups, while education in other areas played no role. Other research has shown that business classes help entrepreneurs better exploit opportunities (Davidsson & Honig, 2003). Managerial experience is seen as leading to knowledge of how to manage people, budgets, and strategy (Chandler & Hanks, 1994). In their meta-analysis, Unger and colleagues (2011) show that general human capital has a small, but significant, positive effect on entrepreneurial performance. Finally, in a meta-analysis on the value of entrepreneurship education and training, Martin, McNally, and Kay (2013) find that it is positively related to entrepreneurial outcomes.

Researchers have also examined the role of more specific human capital investments. These investments are usually seen as investments in industry experience, start-up experience, and task-specific experience. Industry experience is posited to give entrepreneurs knowledge of the industry, its customers, and competitive dynamics (Bosma et al., 2004; Colombo & Grilli, 2005). Prior start-up experience is seen as giving an entrepreneur skills associated with starting a firm, such as obtaining funding, business planning, market building, and the ability to enroll stakeholders (Bruderl et al., 1992; Burns, Barney, Angus, & Herrick, 2015). Further, this experience helps the entrepreneur to learn how to operate under more innovative conditions by building up cognitive tools, such as a willingness to generalize from small samples (Alvarez & Barney, 2007). These entrepreneurs could also develop other decision-making heuristics that can help them operate with limited external information (Alvarez & Barney, 2007; Busenitz & Barney, 1997; McMullen & Shepherd, 2006). Alvarez and colleagues argue:

> Actors who have already gone through this process may not be concerned with the uncertainty of outcomes, or the trial-and-error decision-making process through experimentation. These actors may have acquired the expertise to integrate deep knowledge with broad knowledge and then again with new knowledge required to produce something novel. (2013, pp. 309–310)

Overall, researchers argue that specific human capital investments lead to improved entrepreneurial performance.

Empirical studies largely agree with the prior theory. In research on manufacturing firms, Chandler and Hanks (1994) found that entrepreneurial competence was linked to increased performance. Other researchers have found increased experience in the same industry as the current venture to be a key predictor of that venture's performance. In a longitudinal study of over 1000 new U.S. ventures, Cooper and colleagues (1994) found that increased industry experience was associated with increased firm growth and survival rates. Bosma and colleagues (2004) also found that industry-specific experience was linked to firm survival, profits, and employment growth. Other researchers have found that industry experience increased growth, while experience in industries other than the one the new venture is in had no effect on firm growth (Colombo & Grilli, 2005). Unger and colleagues (2011) call industry and entrepreneurial-specific human capital task-specific human capital because they argue that these experiences are directly related to work in new ventures. They find that task-specific human capital has a stronger effect on performance than general human capital investments (such as education). Overall, this research suggests that investments in specific human capital increase the productivity of entrepreneurs more than investments in general human capital. Further, the more related the prior experience, the better the performance implications in the new venture.

More recently, two studies have called into question the notion that prior specific investments always improve performance, and have examined the role of human capital across different levels of industry innovativeness. Dencker and Gruber (2015) use a measure of industry risk to examine how a set of German entrepreneurs performs in different industries. They find that prior managerial experience is more important in riskier industries, while industry-specific experience is actually harmful in riskier industries. Hmieleski and colleagues (2015) find that education is more important in more dynamic environments, industry specific experience is more important in less dynamic environments, and prior start-up experience is more important in less dynamic industries. However, these researcher still examine each human capital investment as independent, ignoring the possibility that the investments can be either complements or substitutes for each other. If investments depend on each other, this research could be under or over-estimating the importance of different types of investments.

Recent theorizing on human capital in the strategy literature argues that an individual's human capital investments are actually a portfolio, with the value of some investments complementing or substituting for one another, varying across organizational contexts, or acting as signals of a willingness to invest (Campbell, Coff, et al., 2012; Morris, Alvarez, Barney, & Molloy, 2016; Wright, Coff, & Moliterno, 2014). However, if an individual's human capital is a portfolio of different skills gained though different investments, then their human capital investments are not independent. If the outcomes of human capital investments depend on one another, then by examining the interactive effects of human capital, we can begin to better understand how different human capital investments impact performance in a more nuanced way. The next section details our arguments on which human capital investments are complements, and which human capital investments can harm the performance of other investments.

Complementary Human Capital Investments

We argue that an entrepreneur's general human capital investments in education will affect the way that specific human capital investments impact entrepreneurial performance. Individuals will only make investments in education if they will be able to reap the benefits of these investments. Entrepreneurs with more education are likely more talented, and will have developed more diverse knowledge than those with lower levels of education (Becker, 1962, 1993; Weiss, 1995). Eesley and Roberts state that "talent involves more abstract reasoning, divergent thinking, synthesizing disparate ideas, and frame-breaking behaviors" (2012, p. 210). Therefore entrepreneurs with higher levels of education also are more likely to have better critical thinking and reasoning skills than those with lower levels of education. These increased critical thinking and reasoning skills can allow an entrepreneur to be better able to learn from prior specific investments. Entrepreneurs with higher levels of education can better make causal inference and learn from their prior experiences. By gaining a better understanding of an industry's norms, routines, competitors, and dynamics, an entrepreneur should be better able to discover valuable opportunities in the industry. Further, by learning more from their prior start-up experience, they should be better equipped to exploit their chosen opportunities. These entrepreneurs are more likely to use heuristics and biases to make faster decisions (Busenitz & Barney, 1997; Westhead, Ucbasaran, & Wright, 2005). Those with more talent should be better able to generalize from small samples and make better decisions with little to no outside information. Investments in education should improve the performance implications of specific human capital investments, and therefore we hypothesize:

- H1*: Investment in education will moderate investments in a) task-specific experience, and b) prior start-up experience, such that higher levels of education will increase the positive effect of both task-specific and prior start-up experience*

Investments in managerial human capital should also complement specific human capital investments. Managerial human capital helps entrepreneurs learn how to better manage and utilize resources (Chandler & Hanks, 1994). Coupling that with increased knowledge of an industry should allow an entrepreneur to be able to better utilize these resources in a way that can meet the needs of the industry's customers. Further, adding high levels of managerial human capital with prior start-up experience should also enable to entrepreneur to be better able to utilize scarce resources, especially under more uncertain conditions. Further, those who are better able at managing resources should also be better able to enroll stakeholders into their ideas (Burns et al., 2015), improving the performance of subsequent ventures. Therefore we hypothesize:

- H2*: Investment in managerial human capital will moderate investments in a) task-specific experience, and b) prior start-up experience, such that higher levels of managerial experience will increase the positive effect of both task-specific and prior start-up experience*

Investments in education and managerial human capital also impact each other in a complementary way. Those with higher levels of education are better able to reason and think critically. Those with more managerial experience are better able to utilize resources and manage time. When both education and managerial experience are high, individual entrepreneurs should be better able to understand what is needed to succeed—their ability to think and reason critically should improve their utilization of resources, including time management skills. Therefore we hypothesize:

- H3*: Investment in education will positively moderate the positive effect of prior managerial experience*

Noncomplementary Human Capital Investments

Industry-specific task experience should also impact the direct positive effect of prior start-up experience. However, these investments are not complementary—higher investments in one leads to lower performance implications of the other investment. Those with high levels of both industry-specific and prior entrepreneurial experience will have a greater understanding of an industry's norms, competitors, and dynamics (Alvarez & Barney, 2007; Alvarez et al., 2013; Krueger, 2000), but are also much more likely to be overconfident in their own abilities (Busenitz & Barney, 1997). This overconfidence will make the entrepreneur believe they know more than they actually do, and are more likely to dismiss knowledge that does not conform to their prior beliefs. Further, this overconfidence will make them less likely to be able to break the frames they have built through their prior industry experience. Overall, this will reduce the performance effect of future start-ups, as the entrepreneur might land in competency traps (Levitt & March, 1988) and fail to actually learn from their start-up experience. Therefore we hypothesize:

- H4*: Investment in industry-specific task-specific experience will negatively moderate the positive effect of prior start-up experience*

Empirical Setting

To test the hypotheses, we turn to entrepreneurs creating new apps (applications) for the Google Play™ store. We collected data on the developers of all apps listed as 'Top New Apps' in the Google Play™ store on June 10, 2015. This is an important setting in which to study entrepreneurial phenomena. First, with the rise of mobile computing, application development has become a large and growing field. The Google

Play™ store is expected to generate over $5.2 billion in revenue in 2017, not including an estimated $7 billion in ad-generated revenue.[8] Further, many of today's newest growth firms are largely based on mobile applications (for example, Uber, Lyft, and Airbnb). While many of these developers are large, with significant development teams and venture capital backing, a large portion are also independent individuals, which is who this research is focused on. Individual entrepreneurs, working alone, comprise a large, and growing set of entrepreneurs in the U.S. According to the U.S. Census Bureau, there were more than 23 million business in the U.S. without employees in 2013,[9] up about 1% from 2012. These ranged from small corner stores to lawyers (Campbell, Ganco, Franco, & Agarwal, 2012) to mobile application developers. Further, these businesses total $1.1 billion in revenue in 2013,[10] showing that these are important individuals to capture and understand in the entrepreneurial literature. Finally, this growth is happening at a time when traditional job growth is also growing--individuals are choosing to go it alone even when there are other opportunities available.[11]

With each app, Google lists the developer and their email address. Once we captured the developer email addresses, we sent out a survey instrument to capture data about the entrepreneur's human capital investments and their perceptions of the information conditions in which they were operating. The survey was designed to capture information on a variety of human capital investments. These included: education level, years of managerial experience, prior number of apps developed (not at

[8] http://bgr.com/2013/11/19/google-play-annual-revenue/
[9] http://www.bizjournals.com/prnewswire/press_releases/2015/05/27/DC18217
[10] http://www.intelligenthq.com/social-business-2/the-rise-of-the-solo-preneur/
[11] http://www.forbes.com/sites/elainepofeldt/2015/05/30/how-bold-entrepreneurs-are-breaking-1-million-in-one-person-businesses/#43880d01ec12

the current organization), and number of prior start-ups founded. We further capture information on the individual's organization. We ask if the entrepreneur is considered an owner, whether or not they worked alone on the app, and the size of the development team. We also capture data on the financing of the app, including the amount of money raised, and where the funding comes from. The latter includes banks, venture capital, credit cards, crowdfunding, friends and family, government grants, from other businesses, or personal savings.

Overall, we sent out 9577 surveys and received 946 usable responses, for a response rate of 9.5%. Nonrespondents had similar levels of performance from respondents, so we feel that nonresponse bias is not an issue. For this study, the sample was further reduced to focus on respondents who were individual entrepreneurs. This was done because the survey only captured human capital data on the respondent, and not on their team. If the respondent worked in a larger team, then the unobservable human capital attributes of the team could bias the results (Hmieleski et al., 2015). A developer was considered an individual entrepreneur if they worked alone on the development of the app, the organization had only one member, and the individual was considered the owner of the organization. These organizations do not need to be formal legal entities to be included. This led to a sample size of 362 individual entrepreneurs.

There are several reasons that our context is a great test-bed for human capital theory in entrepreneurship. First, we are able to isolate the effects of an individual's human capital investments by examining solo entrepreneurs, removing the confounding effects of entrepreneurial teams. Examining the effects of a founder's human capital without controlling for the human capital of the entrepreneurial team could bias results

(Dencker & Gruber, 2015; Hmieleski et al., 2015). Second, due to the low cost of entry, we are able to capture entrepreneurs that other research designs cannot. In many cases, our entrepreneurs do not have formal firms, and therefore would not show up in many firm-level datasets. This helps alleviate some issue with left censoring found in other entrepreneurial studies. Third we have a unique measure of entrepreneurial performance. Since many entrepreneurial firms have no profits, survival, sales growth, or employment growth are often taken as measures of performance. However, not all entrepreneurs are attempting to grow as fast as possible, and some have other motives that might not be tied to monetary value creation, but rather other forms of stakeholder value (Rindova, Barry, & Ketchen, 2009). Our dependent variable allows us to capture entrepreneurs who are creating value that goes beyond money. Finally, the Google Play™ store operates across the globe, and people from any country can create an app that can be downloaded by anyone, anywhere. Therefore, we have a single marketplace where everyone competes for the same customers, rather than country or region specific marketplaces.

Measures

Dependent variable. The dependent variable in this analysis is a measure of entrepreneurial performance. For app developers, we chose to use the number of weekly installs the app receives in the Google Play™ store for the first 33 weeks[12] of the app's life (approximately 8 months after launch), starting after the survey of the entrepreneurs was sent out. We chose to focus in installs because this allows us to examine entrepreneurs who choose to develop and promote free applications, who would be

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[12] Due to a change in the format of the Google Play store during week 6, we lost performance data for this particular week.

missing if we looked solely at financial performance. Unfortunately, Google does not give the actual number of installs, but rather gives a range. Therefore, our dependent variable is an ordered-category of installs. To ease interpenetration of our results, we combined the install categories (1-9, 10-99, 100-999, 1000+), and labelled them 1-4.

Independent variables. The first set of explanatory variables for this analysis is several measures of different human capital investments. To measure general human capital we used investments in education, general work experience, and managerial experience, as the skills gained through these investments are valuable for many types of organization. We asked each entrepreneur what level of education they had completed at the beginning of developing their app. These were listed as: less than high school, high school, some college, associate's degree, bachelor's degree, master's degree, and doctorate. These were then coded into years of education, and standardized to simplify interpretations. The average level of education in our sample was 15.3 years, indicating the average entrepreneur had almost completed a bachelor's degree. For managerial human capital, we asked each entrepreneur how many years of managerial experience they had. This ranged from 0 to 30. The average entrepreneur in our sample had 2.4 years of managerial experience.

For specific human capital, we asked each respondent how many apps they have had a significant role in developing. This ranged from 0 to 30. In our sample, about 23% have never developed an app before, while about 15% had developed 15 or more apps in the past. The average entrepreneur in our sample had developed 4.95 previous apps. We also asked the number of prior start-ups the respondent had owned or co-owned. This variable ranged from 0 to 27, and over 35% of our respondents had never owned a start-up in the past, while approximately 7% had owned 10 or more prior businesses. The average entrepreneur had .78 prior start-ups.

Control variables. Following recent research (Dencker & Gruber, 2015; Hmieleski et al., 2015; Raffiee & Feng, 2014), we have controlled for the level of novelty of the opportunity. We do this by examining how unique each app is by utilizing the text description provided by each app's developer. We then compared the text descriptions of our focal apps to all other apps that were on the market in the month prior to our focal apps being released. We then determined a similarity score between each app. Due to the large number of apps in the market, the overall average similarity was small, so we chose to examine the 10 nearest neighbor to our focal app. If the focal app had many similar apps, then the 10 nearest neighbor's descriptions would also be similar. If the app was more unique, then the 10 nearest neighbors would have a low similarity score. Therefore, we included the average similarity of the 10 nearest neighbors to each focal app as a measure of the level of novelty of the specific app.

We also included several controls to rule out alternative explanations. First, it is possible that those with higher levels of funding would perform better, and therefore we surveyed the entrepreneur about the level of funding they received for the development of their app from a variety of sources. For each source, we asked for the level of funding in the following categories: $0, 1-$99, $100-$999, $1000-$9999, $10000-$99999, $100000+. The funding sources included were personal savings, credit cards, money from other businesses, friends and family, crowd funding, bank financing, or venture capital. We then summed these and used the minimum financing amount as our control.

Following previous literature, we also controlled for the entrepreneur's motivation. The survey asked entrepreneurs why they developed the app, and coded a '1' if they responded they wanted to get as many installs as possible. We also controlled for whether or not the entrepreneur was working full or part-time on their app. We did this by including a dummy variable that equals '1' if the individual was working full-time or wanted to work full-time for their development organization. Our results are robust to alternative specifications of this control variable.

Finally, we also used several app-specific controls that could affect performance. First, we used a binary indicator to control for if the app was a paid app or free. We also utilized a binary dummy code if the app offered in-app purchases. We also controlled for the category of the app by utilizing a binary control for the games category, as these types of apps are likely to have a broader audience. We controlled for the time the application has been on the market (in days), as longer availability could increase the number of installs. We also controlled for whether or not the entrepreneur is in the U.S. with a binary indicator. We also controlled for the games category, as these apps could be targeted at a broader audience and achieve higher levels of installs.

Methods

To test our hypotheses, we used ordered logistic regression, with time fixed-effects, since the dependent variable is an ordered categorical variable (Wooldridge, 2010). Further, we utilized robust standard errors to control for possible heterogeneity in the errors (Huber, 1967; White, 1980). We tested for multicollinearity using regression and variance inflation factors (VIF). Results showed that there was possible multicollinearity due to the interactions of the human capital variables. Therefore, we mean-centered all human capital variables, and reran our multicollinearity tests. These results indicated that all VIFs were now under 3, indicating that we had no further issues with multicollinearity. We will therefore present and interpret models with mean-centered human capital variables.

Results

Summary statistics are included in Table 3.1. Note that the level of financing for these developers is small and not strongly correlated with installations. This is due to the low cost of entry into this market. This removes a large alternative explanation, that performance in this context is based largely on the level of outside resources. Further, over 85% of our respondents say that achieving as many installs as possible is important to them. Further, while only about 17% of our sample work full-time for their current organizations, about 50% are working on their app part-time but looking to make it a full-time job. Taken together, this shows that achieving strong levels of performance is important to these entrepreneurs, and suggests that this market is reasonably competitive.

Table 3.2 shows our ordered-logistic regression results. Model 1 is the control model. All controls are included in main regression models, and act largely in expected ways. Model 2 adds the human capital investments and also controls for the opportunity-specific innovation level. Results would indicate that education and prior start-up experience have negative and significant direct impact on performance, while prior managerial experience and prior industry-specific task experience (the number of prior apps developed) directly (and significantly) improve performance. However, this model assumes that all of the human capital investments act independently to affect performance.

Model 3 adds the interactions between the various human capital investments. When the interactions are added, we see a different story. We see that education has an impact on prior industry-specific task experience. The coefficient is positive and highly significant (p<.001). This indicates that increased task experience has a greater impact on performance for those with higher levels of education. This provides supports H1a. We find the opposite of our prediction in H1b, as education seems to have a negative and significant effect on prior start-up experience. We also found the opposite of our prediction in H2a, since managerial experience has a negative and significant impact on prior industry-specific task experience. However, we find support for H2b. Managerial experience and prior-start-up experience are complements. Increased prior start-up experience has a stronger impact on performance when managerial human capital is also high.

We find that managerial experience and education are complements, with the interaction term being negative and significant (p<.05). For entrepreneurs with high levels of education, having higher levels of managerial experience improves performance. This lends support for our prediction in H3. Finally, we also find that industry-specific task experience and prior start-up experience are not complementary. The coefficient on this interaction is negative and highly significant (p<.001). This lends support for H4.

To gain a better understanding of our results and to see the size of our effects, we ran marginal analysis to predict the probability of getting between 1000 or more installs for varying levels of prior investments. Only 39.5% of apps get 1000+ installs, and only

22.6% ever get more than 5000 installs, so we feel that this is an appropriate measure of success for our sample. To calculate our margins, we examined each human capital investment at their average, and plus/minus one standard deviation. Figures 3.1 and 3.2 show the interaction between education and our two measures of specific human capital. As shown in Figure 3.1, high levels of education greatly improve the relationship between industry-specific task experience and performance. An entrepreneur with low education and high task related experience only has a 32.6% chance of achieving 1000 or more installs, but this chance rises to 40.6% for those with high levels of education. Figure 3.2 shows that at low levels of education, having more prior start-up experience does not significantly improve performance. However, when education is high, high levels of prior start-up experience actually lead to lower performance—the entrepreneur only has a 22% chance at getting 1000 or more installs, compared to a 30.3% chance when they have high education and low prior start-up experience..

Figures 3.3 and 3.4 show the interactions between managerial experience and our measures of specific human capital. Figure 3.3 shows the relationships between managerial experience and industry-specific task experience. As shown, having high levels of both managerial and task-related experience actually leads to the best performance. While the interaction between the investments is negative, the main effects are both positive, leading to the conclusion that increases in managerial experience have a larger impact on performance for lower levels of task-specific investments. For low levels of task-experience, increases from low to high levels of managerial experience lead to a 58.8% increase in the probability of achieving 1000 installs, where for high levels of task experience, increasing from low to high managerial experience only leads to a 27.4%

increase in the probability of achieving 1000 or more installs. Figure 3.4 shows how prior start-up experience is impacted by different levels of managerial experience. Again, we see that increases in both investments lead to increased performance. At low levels of managerial experience, we see that increased prior start-up experience leads to lower performance, whereas at high levels of managerial experience, this relationship changes such that higher levels of prior start-ups leads to increased performance.

Figure 3.5 shows the interaction between education and prior managerial experience. As shown, these investments act as a complement with each other, with high levels of both leading to better overall performance. For entrepreneurs with low levels of education, increases in managerial experience lead to increased performance, going from a 28.8% chance of getting 1000 or more installs to a 31.2% chance, an increase of 8.1%. However, with high levels of education, increases in managerial experience actually lead to even better performance. Here, the chance of getting 1000 or more installs increases from 24.5% to 35.8%, a 46.4% increase.

Figure 3.6 shows the results for the interaction between industry-specific task experience and prior start-up experience. The interaction between these investments is negative. For entrepreneurs with the lowest level of task experience, increases in prior start-up experience lead to slightly lower performance, going from 24.8% to a 23.4% chance at achieving 1000 or more installs, a 5.5% decrease. However, for those with high task experience (which has a strong, positive impact on performance), increases in prior start up experience lead to an increasing lower chance of achieving 1000 or more installs. At high levels of task experience and low levels of prior start-ups, an entrepreneur has a 37.5% chance at achieving 1000 or more installs, and this falls to

33.2% for high levels of prior start-up experience, an 11.5% drop. This shows that an entrepreneur is better off having high task related experience, and lower levels of prior start-up experience.

Additional Tests

To both validate our results and further explore our findings, we ran several additional tests and robustness checks. First, we ran models with the full install categorization scheme. These results were consistent with our findings. Second, we ran another alternative measure of performance, a dummy variable indicating that an app received 1000 or more installs. These results were also largely consistent with those presented (however we lost significance for the managerial experience-industry-specific task experience interaction). Finally, we tested an alternative measure of app innovativeness. We used the results from our developer survey to measure of the average level of app innovation. When including this as a control instead of our text description similarity measure, we found largely the same results, with the exception of the interaction between education and managerial experience losing significance.

Next, we ran a model to further examine our surprising finding on education. We predicted that education would improve the effects of both prior app development and prior start-up experience. However, we found education positively impacted app development experience and negatively impacted prior start-up experience. One potential reason is that, in our context, technical skills are more associated with prior app development, while not necessarily suited to running businesses. Therefore, we broke years of education into two distinct types: technical and nontechnical. Technical education comprised of years of education in computer science, engineering, or natural science. Nontechnical education comprised all other types of education. In our sample, about 59% had education in more technical areas. However, as seen in Table 3.3, we saw similar patterns for those with technical versus nontechnical education—all education improves the value of prior app development experience. One possible explanation for this finding is the possibility of unobservable education that is confounding our result. For example, while those with technical education might be able to easily learn to develop mobile apps, those without might be taking training courses or other classes to learn app development. For these, nontechnical education might improve their ability to learn from these unobservable courses. Finally, we saw no type of education improves learning from prior start-ups. It is possible that, since this learning is noisy and ambiguous, education by itself does not help learning in these environments. Further research is needed to better explore the role of education in learning from other experiences.

Second, we examined the top performers—those with 10000 or more installs. Different types of human capital investments could impact performance of the most successful individuals differently than for those with more moderate levels of performance. We therefore examined a model to see if human capital impacts performance differently for those who achieve 10000 or more installs (the top 20%). We used the full categorization scheme as our dependent variable in order to capture those with extremely high performance. We then ran quantile regression on the 80th

percentile.[13] Results are in Table 3.4. Largely, results were consistent with previous models. We found no significance for both the education/prior app experience and the managerial experience/prior start-up experience interactions. Future research should continue to investigate to better understand the differences between top performers and the average performers.

Finally, we also ran an additional test on the subset of our data comprising entrepreneurial teams. Following prior research (Hmieleski et al., 2015), we did not collect the human capital investments of the team, but we did have the responses of the founders of these teams. Additionally, we added a control for team size. When we examined the how human capital investments interact for these founders, we saw slightly different results. Table 3.5 shows that some investments are not significant. Again, we found no significance for both the education/prior app experience and the managerial experience/prior start-up experience interactions. Here, it could be that other individuals on the team are substituting or complementing their prior experience for that of the founder.

Discussion and Conclusion

This research examined whether or not investments in entrepreneurial human capital were independent, or if the performance implications of some investments depended on the level of other investments. We found that education has no direct effect on performance, while higher levels of prior industry-specific task experience and

[13] Additional models suggest that running our tests with ordered logistic regression, regressions, and median regression all have substantively similar results, so we feel that this is an appropriate test for these top performers.

managerial experience led to improved performance, and higher levels of start-up experience led to lower performance. Following previous research, we would draw incorrect conclusions about the impact of these investments. However, by examining the interactions between different investments, we found that some human capital investments are complements, while others were not complementary. Specifically, we found that higher levels of education positively impacted the performance implications for industry-specific task experience, but had a negative impact on prior start-up experience. More prior apps developed improved performance on the current app, and this benefit is increased when the entrepreneur has higher levels of education, while more prior start-up experience harmed performance as education rises. In our additional tests, we found this result did not depend on whether or not the individual's education was in a technical field or not. This suggested that there were some unobservable training or education that our measures are not capturing that could affect the ability of our entrepreneurs to learn from prior app development experience, but not prior start-ups (for example, formal or informal courses in app development or programming). Future studies should further examine what role informal education plays the build-up of other types of human capital and skills. We also found that higher levels of prior managerial experience complemented more prior start-up experience but negatively impacted task-specific experience. It is likely that the knowledge gained through managerial experience was better for managing future ventures than in the development of technical skills in our context, where technical knowledge is likely to be highly valuable. We also found that the two types of general human capital investments, education and managerial experience, acted as complements. Higher levels of both of these types of investments led to higher performance. Entrepreneurs with more education were better able to learn from their managerial experience.

We found that high levels of both types of specific investments are not complementary. Entrepreneurs with more industry knowledge can develop deep beliefs (Krueger, 2000) about an industry and be locked into a set of norms and routines of doing business that might not translate to their new venture. Adding to this, their increased prior start-up experience, which leaves them likely overconfident (Busenitz & Barney, 1997; Westhead et al., 2005) in their own ability. This overconfidence, coupled with deep beliefs, could lead the entrepreneur to be unable to break the frames they developed in the past, hurting performance in their new venture, as they are likely to dismiss non-confirming information that could help them improve their venture's performance.

This research makes several contributions to the entrepreneurship literature. First, we add to the growing literature on human capital and entrepreneurial performance. Previous research has shown that human capital has a positive (Bates, 1990; Bosma et al., 2004; Bruderl et al., 1992; Colombo & Grilli, 2005, 2010; Cooper et al., 1994; Davidsson & Honig, 2003), but small impact on entrepreneurial performance (Unger et al., 2011). We build on this by showing that human capital investments do not act in isolation, and in fact, the performance implications of these different investments depend on levels of other investments. For example, Unger and colleagues (2011) found that specific investments have a stronger relationship with performance than general investments. While Unger and colleagues (2011) call for more testing of key moderators, they do not argue that these investments might actually moderate each other. Our results point to one potential reason for their low correlation between education and performance—

education actually improves the performance on industry-specific task human capital investments. Further, our results also show that some investments do not complement each other, and in fact higher levels of some general investments actually lead certain specific investments to be less valuable to entrepreneurial performance. By examining investments in isolation, prior research might be understating the importance of general human capital investments, and understating or overstating the importance of specific human capital for entrepreneurial performance.

We also add to the recent human capital studies by Dencker and Gruber (2015) and Hmieleski and colleagues (2015). These studies examine how a founder's human capital investments impact performance across different levels of industry risk or dynamism. In our study, while we examine a single industry, we do include a measure of opportunity specific novelty, since entrepreneurs within an industry can still be exploiting more or less novel opportunities (Raffiee & Feng, 2014). Further, our study had removed any confounding effects of the entrepreneurial team. Finally, we add to their studies by showing that entrepreneurial human capital investments are not independent. Future studies should examine how an entrepreneur's portfolio of investments impacts performance across both risky and uncertain contexts (Alvarez & Barney, 2007; Alvarez et al., 2013).

Our findings also add to recent theorizing in strategy. Individuals do not make choices on what types of human capital to invest in individually, but may actually think about the overall portfolio of investments they currently have and need to succeed in their careers (Campbell, Coff, et al., 2012; Wright et al., 2014). Other researchers have argued that that general and specific investments are not independent, but they focused on the signaling value of specific investments. They argue that investments in firm-specific human capital are signals to the market on an individual's willingness to make these types of investments, which is a form of general human capital (Morris et al., 2016). This paper goes a step further, and shows that, in fact, the performance implications of general and specific investments depend on each other—they are not independent. Researchers examining how different types of human capital impact performance of teams and organizations would be advised to examine the entire portfolio of investments (Campbell, Coff, et al., 2012; Morris et al., 2016; Wright et al., 2014), as examining each investment independently could lead to biased results.

Our results are generalizable in several ways. First, we feel that our findings can be generalized to other entrepreneurs working in other industries, especially high-tech industries. In these industries, entrepreneurs often call upon the same skills and human capital investments that our entrepreneurs have (education, managerial experience, app design experience, and prior start-up experience). We feel that our results should hold in these other areas. Further, we feel that our results can also extend to individuals working in larger organizations. Individuals in larger firms also have a portfolio of human capital investments. It is likely that investments in general human capital will also improve the team or organizational performance implications of these individual's firm-specific investments. For example, an individual with higher levels of education might be better able to or more quickly learn the tacit norms and routines of a firm, and could possibly even make these routines more efficient. This is a fruitful avenue for strategy and human capital researchers in the future.

Like all work, there are also several limitations to our study. First, as with all surveys, we rely on the responses of the entrepreneurs. To help reduce common method bias, we utilize a nonsubjective dependent variable, the number of installs the app receives after the initial human capital survey. Further, we ask about human capital investments, rather than the entrepreneur's perceptions of the outcomes of those investments, which could be more subject to bias than the more objective investments. Second, we do not know the order in which the human capital investments were made. It could be that the order matters, and that early general human capital investments increase the implications of later specific investments, or that simultaneously investing in general and specific leads to increased benefits. Future studies should examine this to gain a better understanding of how the timing of investments improves performance.

This research also leads to several other fruitful avenues for future research. In our additional tests, we found that the performance effect of a founder's human capital investments relationship between human capital and performance varied for entrepreneurs working alone versus working in teams. These tentative results suggest a limitation of prior research, which might have confounded the effects of a founder's human capital with that of the entrepreneurial team (Hmieleski et al., 2015). Future research should examine to see if different human capital investments of a founder's team act as substitutes or complements to the founder's human capital. Another fruitful avenue of research would be to examine how an entrepreneur's human capital portfolio affects performance under different entrepreneurial contexts. Recent research (Dencker & Gruber, 2015; Hmieleski et al., 2015) has shown that human capital impacts performance differently across conditions of risk and uncertainty (Alvarez & Barney, 2007; Alvarez et al., 2013). Therefore, we believe that it will be important to examine how an entrepreneur's portfolio of human capital impacts performance differently across these conditions.

There are several implications to this study for both entrepreneurs and practicing managers. For entrepreneurs, this research points out that in some instances, more investments in human capital do not lead to improved performance, especially with high levels of both industry-specific task experience and prior start-up experience. Having high levels of both of these could lock an entrepreneur into a suboptimal way of thinking about an industry, and lead to increased overconfidence in their ability (Busenitz & Barney, 1997). This could lead to lower performance for the entrepreneur. For practicing managers, our research implies that when examining individuals, managers must look at all of their skills, not only a single type of investment in isolation. When managers are looking to add individuals to their organization, they should think about how their overall skills portfolio could help the organization succeed.

In conclusion, this research has shown that an entrepreneur's human capital investments are not independent, and in fact, the performance effects of investments depend on the level of other investments. We find that some of an entrepreneur's general human capital investments improve the performance implications of their industry-specific task and prior start-up experience, while other types of investments reduce the value of specific investments. We also find that higher levels of both education and managerial experience lead to higher performance. Finally, we find that high levels of both industry-specific task experience and prior start-up experience lead to lower entrepreneurial performance. When examining human capital investments, both researchers, managers, and entrepreneurs should remember that these investments are not independent, but impact each other.

Table 3.1

Summary Statistics for Mobile Application Developers

Variables	*N*	mean	*sd*	min	max
Install Category	11472	3.04	0.89	1	4
Education (years)	11472	15.37	2.59	10	20
Managerial Exp. (years)	11472	2.55	4.62	0	30
Prior # Apps Developed	11472	4.77	6.97	0	30
Prior # Start-Ups	11472	0.76	1.73	0	20
Innovation Measure	10701	0.16	0.09	0.01	0.89
Financing Amount	10703	364.33	2009.26	0	20100
Paid	11472	0.08	0.28	0	1
Offers In-App	11472	0.10	0.30	0	1
Country=USA	11472	0.29	0.46	0	1
Purpose	11472	0.85	0.36	0	1
Full Time	11472	0.61	0.49	0	1
Time on Market	11472	101.69	81.71	0	575
Game	11472	0.32	0.47	0	1
Wave	11472	17.01	9.49	1	33

Table 3.2

Ordered Logit Models for Install Categories, Solo Entrepreneurs

VARIABLES	Model 1	Model 2	Model 3
Education		**-0.060****	**-0.011**
		[0.019]	[0.022]
Managerial Experience		**0.254*****	**0.221*****
		[0.027]	[0.030]
Prior # Apps Developed		**0.339*****	**0.349*****
		[0.034]	[0.037]
Prior # Start-Ups		**-0.078***	**-0.104****
		[0.033]	[0.038]
Education X Prior # Apps			**0.152*****
			[0.036]
Education X Prior # Start-Ups			**-0.178*****
			[0.030]
Managerial Exp. X Prior # Apps			**-0.122****
			[0.045]
Managerial Exp. X Prior # Start-Ups			**0.161*****
			[0.028]
Education X Managerial Exp.			**0.089****
			[0.028]
Prior # Apps X Prior # Start-ups			**-0.076*****
			[0.020]
Innovation Measure	**2.588*****	**1.568*****	**1.643*****
	[0.305]	[0.301]	[0.309]
Financing Amount	**0.000*****	**0.000*****	**0.000*****
	[0.000]	[0.000]	[0.000]
Paid	**-2.741*****	**-2.767*****	**-2.764*****
	[0.078]	[0.080]	[0.080]
Offers In-App	**0.640*****	**0.681*****	**0.709*****
	[0.061]	[0.064]	[0.066]
Country=USA	**-1.541*****	**-1.602*****	**-1.618*****
	[0.047]	[0.048]	[0.048]
Purpose	**0.627*****	**0.595*****	**0.597*****
	[0.054]	[0.054]	[0.056]
Time on Market	**-0.008*****	**-0.008*****	**-0.008*****
	[0.000]	[0.000]	[0.000]
Games	**0.124****	**0.119****	**0.146****
	[0.043]	[0.044]	[0.045]
Wave Fixed Effects	*Included*	*Included*	*Included*
Observations	9,964	9,964	9,964
Log Likelihood	-10158	-10045	-9988
Pseudo R-Squared	0.168	0.177	0.182

Robust standard errors in brackets

**** p<0.001, ** p<0.01, * p<0.05, + p<0.1*

Table 3.3

Ordered Logit Models for Install Category, Team Entrepreneurs

VARIABLES	Model 1
Education (yrs.)	**0.025****
	[0.008]
Managerial Exp. (yrs.)	**-0.066*****
	[0.004]
Prior # Apps Developed	**0.048*****
	[0.003]
Prior # Start-Ups	**0.007**
	[0.012]
Education X Prior # Apps	**0.002**
	[0.001]
Education X Prior # Start-Ups	**-0.011****
	[0.004]
Managerial Exp. X Prior # Apps	**-0.001*****
	[0.000]
Managerial Exp. X Prior # Start-Ups	**0.008*****
	[0.001]
Education X Managerial Exp.	**-0.001**
	[0.001]
Prior # Apps X Prior # Start-ups	**-0.018*****
	[0.001]
Innovation Measure	**-1.754*****
	[0.329]
Team Size	**0.001**
	[0.005]
Controls	*Included*
Wave Fixed Effects	*Included*
Observations	10,498
Log Likelihood	-9765
Pseudo R-Squared	0.229

Robust standard errors in brackets
**** p<0.001, ** p<0.01, * p<0.05, + p<0.1*

Table 3.4

Ordered Logit Models for Install Category, Expanded Education

VARIABLES	Model 1
Technical Education (yrs.)	**-0.056****
	[0.019]
Nontechnical Education (yrs.)	**0.019**
	[0.013]
Managerial Exp. (yrs.)	**0.025*****
	[0.005]
Prior # Apps Developed	**0.041*****
	[0.005]
Prior # Start-Ups	**-0.009**
	[0.027]
Tech Education X Prior # Apps	**0.010****
	[0.003]
Tech Education X Prior # Start-Ups	**-0.069*****
	[0.013]
Nontech Education X Prior # Apps	**0.007****
	[0.002]
Nontech Education X Prior # Start-Ups	**-0.021***
	[0.010]
Managerial Exp. X Prior # Apps	**-0.002***
	[0.001]
Managerial Exp. X Prior # Start-Ups	**0.013*****
	[0.002]
Tech Education X Managerial Exp.	**0.019*****
	[0.004]
Nontech Education X Managerial Exp.	**0.001**
	[0.002]
Prior # Apps X Prior # Start-ups	**-0.006*****
	[0.001]
Innovation Measure	**1.750*****
	[0.344]
Controls	*Included*
Wave Fixed Effects	*Included*
Observations	9,964
Log Likelihood	-9969
Pseudo R-Squared	0.184

Robust standard errors in brackets
**** p<0.001, ** p<0.01, * p<0.05, + p<0.1*

Table 3.5

80th Percentile Regression Models for Install Category

VARIABLES	Model 1
Education (yrs.)	**0.006**
	[0.012]
Managerial Exp. (yrs.)	**0.028*****
	[0.003]
Prior # Apps Developed	**0.028*****
	[0.005]
Prior # Start-Ups	**-0.083*****
	[0.017]
Education X Prior # Apps	**0**
	[0.003]
Education X Prior # Start-Ups	**-0.023*****
	[0.003]
Managerial Exp. X Prior # Apps	**-0.001***
	[0.000]
Managerial Exp. X Prior # Start-Ups	**0**
	[0.002]
Education X Managerial Exp.	**0.017*****
	[0.001]
Prior # Apps X Prior # Start-ups	**-0.005*****
	[0.001]
Innovation Measure	**5.199*****
	[0.314]
Controls	*Included*
Wave Fixed Effects	*Included*
Constant	**5.617*****
	[0.091]
Observations	9,964
R-Squared	0.342
Log Likelihood	

Robust standard errors in brackets
**** p<0.001, ** p<0.01, * p<0.05, + p<0.1*

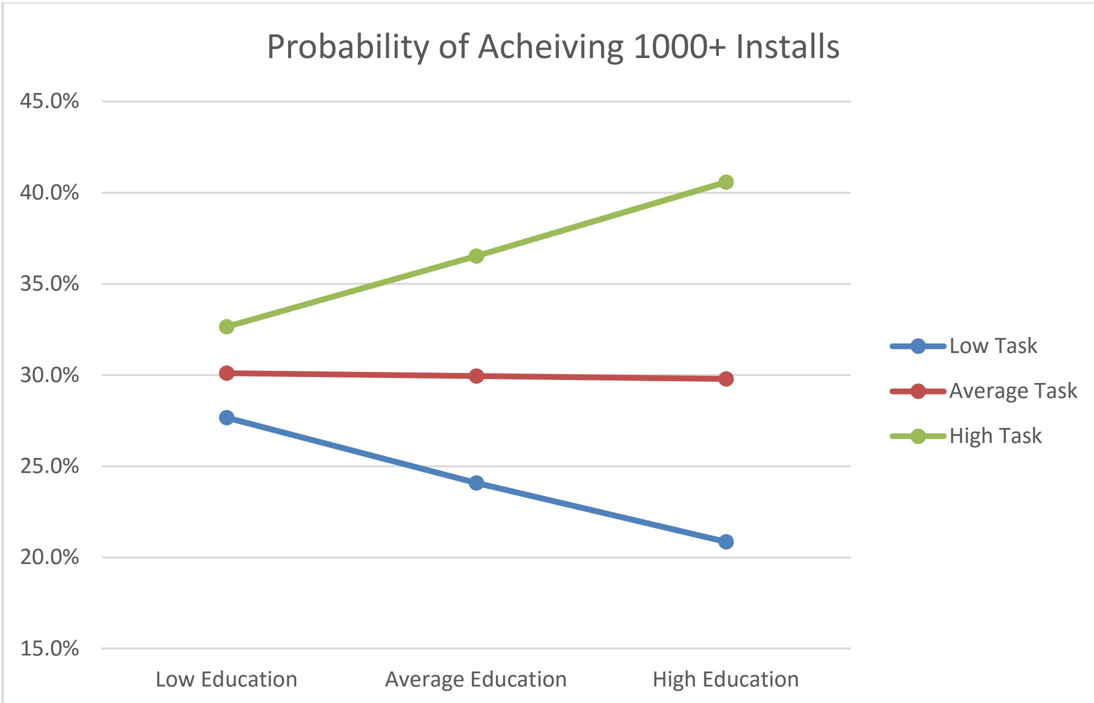

Figure 3.1: Education and Industry-Specific Task Experience Interaction

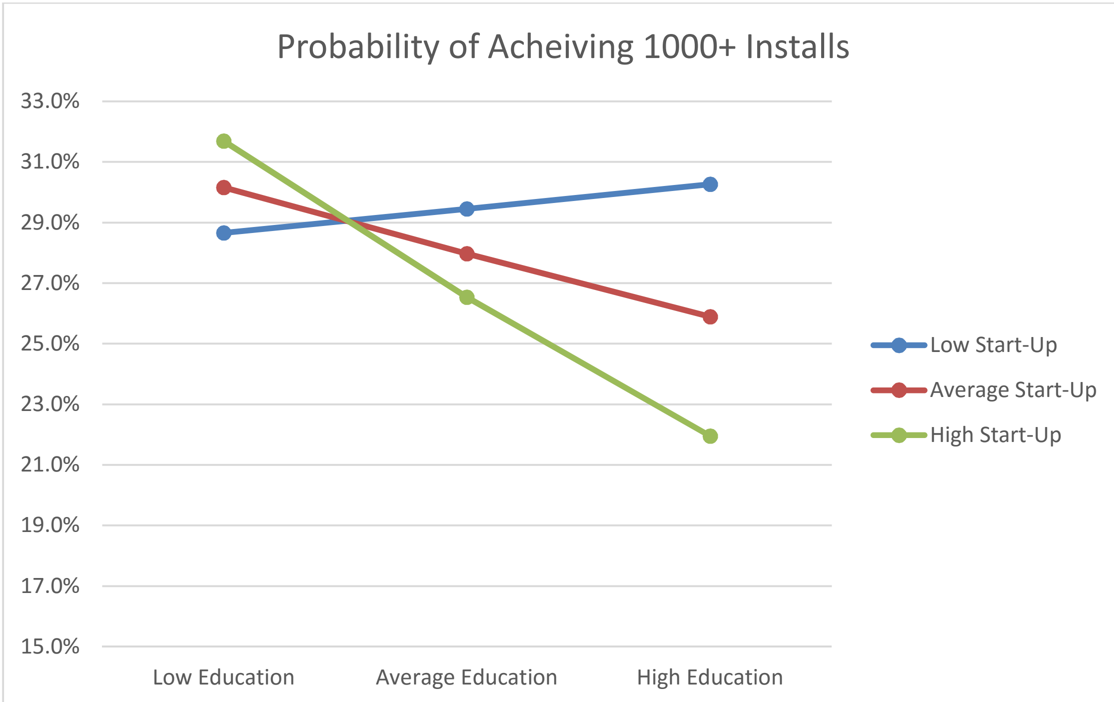

Figure 3.2: Education and Prior Start-Up Experience Interaction

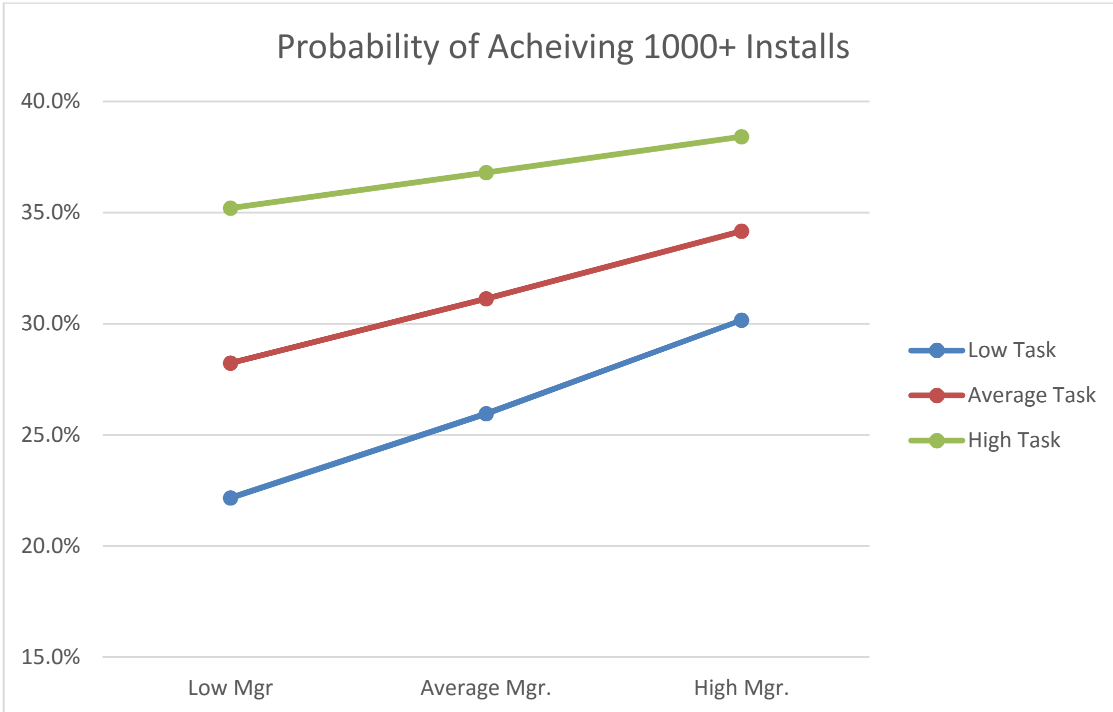

Figure 3.3: Managerial Experience and Industry-Specific Task Experience Interaction

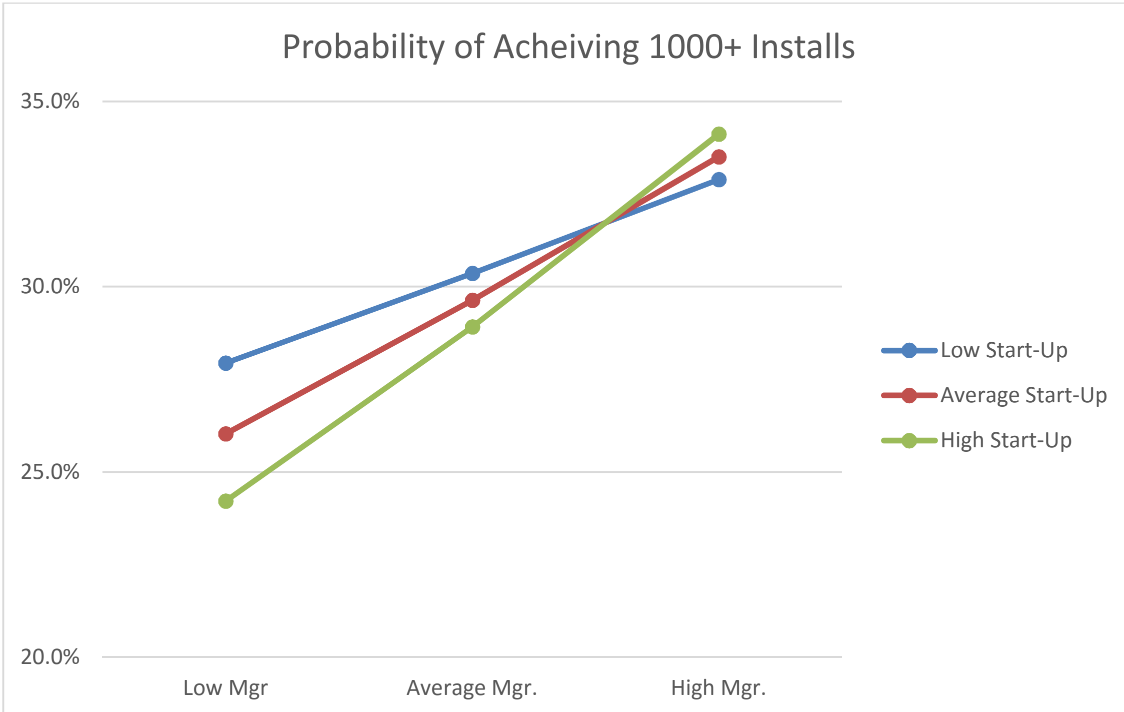

Figure 3.4: Managerial Experience and Prior Start-Up Experience Interactions

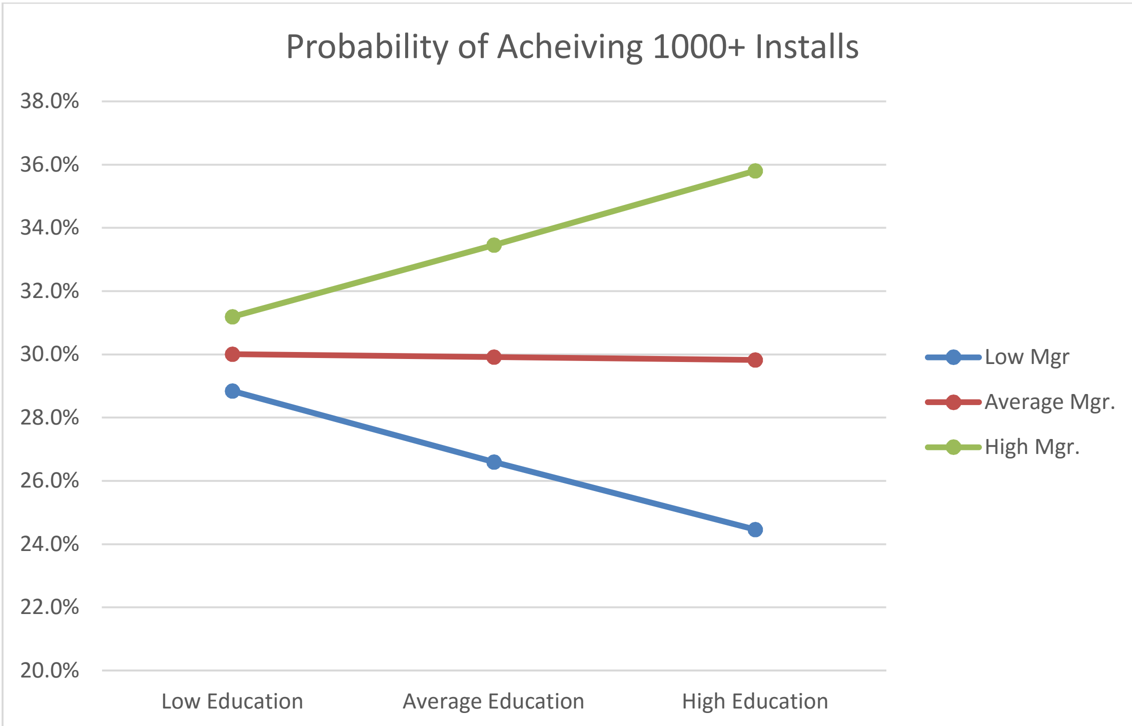

Figure 3.5: Managerial Experience and Education Interaction

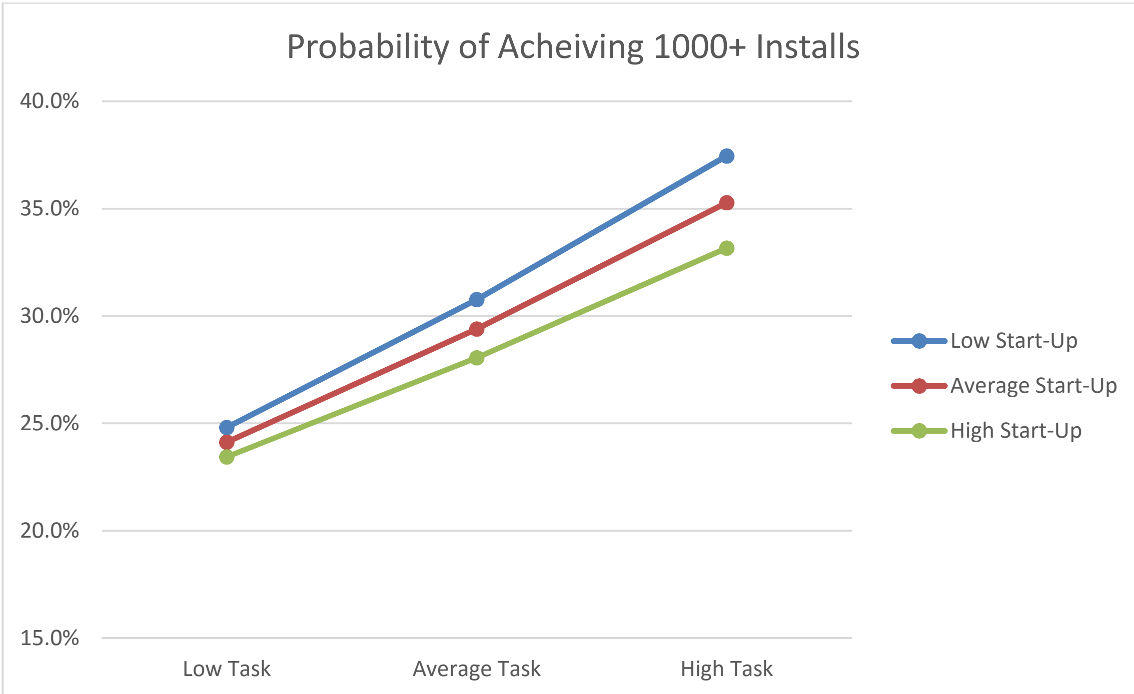

Figure 3.6: Industry-Specific Task Experience and Prior Start-Up Experience Interaction

CHAPTER 4

EXPERIENCED VERSUS NOVICE ENTREPRENEURS AND EFFECTIVE ENTREPRENEURIAL ACTION

Introduction

Researcher have been increasingly interested in the performance differences between novice and experienced entrepreneurs. The entrepreneurial enactment process can change the thinking and assumptions of entrepreneurs, such that experienced entrepreneurs "may have acquired the expertise to integrate deep knowledge with broad knowledge and then again with new knowledge required to produce something novel" (Alvarez et al., 2013, p. 310). Further, prior entrepreneurial experience is argued to build entrepreneurial human capital, defined as the ability to create, identify, and exploit opportunities (Westhead et al., 2005; Westhead, Ucbasaran, & Wright, 2009). This experience has been shown to shape an entrepreneur's cognition and thinking, such that experienced entrepreneurs make decisions differently than novice entrepreneurs (Busenitz & Barney, 1997; Dew, Read, Sarasvathy, & Wiltbank, 2009; Dew et al., 2009; Westhead et al., 2005). Early empirical studies have shown that prior start-up experience is a strong predictor of entrepreneurial success (Bosma et al., 2004; Chandler & Hanks, 1994; Delmar & Shane, 2006; Parker, 2013; Unger et al., 2011), yet more recently, other researchers have found that prior entrepreneurial experience either has no relationship or hurts the performance of an entrepreneur's current venture (Hmieleski et al., 2015; West & Noel, 2009). Therefore, researchers do not have a definitive answer to how prior start-up experience impacts current venture performance.

However, one less studied aspect of the relationship between prior entrepreneurial experience and performance is how this prior entrepreneurial experience shapes the actions that novice and experience entrepreneurs use to exploit their opportunity, especially for different types of opportunities (Alvarez & Barney, 2007, 2010; Alvarez et al., 2013; Venkataraman, 1997). Some entrepreneurs exploit more imitative opportunities, while others exploit more novel, innovative opportunities. Less novel, more imitative opportunities are similar to other opportunities and businesses in the market, and therefore more external information about the opportunity exists (Shane & Venkataraman, 2000). Other entrepreneurs are more innovative, and are exploiting more novel, unique opportunities (Alvarez & Barney, 2007, 2010; Alvarez et al., 2013). For these entrepreneurs, little information exists about their opportunity—there are few similar opportunities already in the market. While recent researchers have shown that prior experience impacts performance differently under these conditions (Dencker & Gruber, 2015; Hmieleski et al., 2015), we know less about how prior experience, especially prior entrepreneurial experience, impacts the effectiveness of the actions that entrepreneurs take when exploiting more or less novel opportunities. Prior research has shown that experienced entrepreneurs think differently than novice, first-time entrepreneurs (Busenitz & Barney, 1997; Westhead et al., 2005), and therefore we should see different performance impacts from different entrepreneurial actions. Further, researchers argue that different actions should be more or less effective for different types of opportunities (Alvarez & Barney, 2007; Alvarez et al., 2013). The differing cognitions of experience entrepreneurs should also impact this effectiveness. By examining the way that entrepreneurial experience moderates different entrepreneurial actions, we can begin to better understand the process in which entrepreneurs exploit more or less novel opportunities.

This research will examine how different entrepreneurial actions impact performance for both novice and experienced entrepreneurs, under different levels of opportunity novelty. Novice entrepreneurs are those who have no prior start-up experience, while experienced entrepreneurs have one or more prior start-ups. Prior start-up experience is suggested to be one of the best ways in which entrepreneurs can learn to handle uncertainty, and improve future performance of more novel opportunities (Alvarez & Barney, 2007; Alvarez et al., 2013). This paper will argue that prior start-up experience moderates the relationship between two distinct entrepreneurial actions and performance: environmental scanning and prototype testing. Environmental scanning involves learning from external information sources for knowledge of competitors, potential demand, and how to market to consumers (Beal, 2000; Westhead et al., 2009). Prototype testing is the creation of new, opportunity-specific information (Alvarez & Barney, 2007; Alvarez et al., 2013; Brown, 2008; Kelley, 2001; Ries, 2011).

We argue and find support for the notion that, for less novel opportunities, novice entrepreneurs will improve performance by scanning the environment (at least up to a point), but harm their performance by prototype testing. Experienced entrepreneurs will have greater performance benefits for less time spent scanning the environment. However, we find no support for the notion that increased prototype testing leads to improved entrepreneurial performance of less novel opportunities for experienced entrepreneurs, and in fact more prototype testing leads to lower performance for experienced entrepreneurs for these types of opportunities. For more novel opportunities, we find, opposite to our predictions, that increases in environmental scanning actually improve performance for novice entrepreneurs, and we find no support for the argument that prototype testing will improve performance for novice entrepreneurs. For experienced entrepreneurs, we argue and find that increased environmental scanning will lead to improved performance (up to some threshold), and that that increased prototype testing does help experienced entrepreneurs exploit novel opportunities.

This paper will test our hypotheses in a unique survey of Google Play™ app developers. This is a strong setting in which to test the hypotheses for several reasons. First, it has been extremely difficult to measure entrepreneurial performance, especially given that, in the early stages, many firms do not yet have sales and profits. This setting allows for an unbiased estimate of performance – app downloads that compete in the same marketplace. While not a direct financial measure, increased levels of downloads are associated with higher revenue, as many apps have a set price per download or offer in-app purchases. Second, there are few barriers to entry in this setting, and therefore there are a large number of entry events, with relatively short market duration in which to examine performance. We develop a novel survey instrument that captured both prior human capital investments and the actions that the entrepreneurs undertook before launching their apps on the market. Finally, our setting allows for a clean test of human capital and entrepreneurial action theory, as we can isolate individual entrepreneurs from entrepreneurial teams, which could lead to confounding results (Hmieleski et al., 2015).

The next section reviews the literature on experience versus novice entrepreneurs, and entrepreneurial action. We then develop our hypotheses regarding how the performance implications of different actions vary with experienced versus novice entrepreneurs. We then describe our empirical setting, data, and methodology. We then present our results, followed by our discussion and conclusions.

Performance Impact of Entrepreneurial Experience

Recent theorizing in entrepreneurship argues that some individuals exploit opportunities that are more novel than other individuals do (Alvarez & Barney, 2007; Alvarez et al., 2013). For less novel opportunities, entrepreneurs are largely imitating other opportunities in the market, and information about these other opportunities exists to help the entrepreneurs make predictions about the value of their opportunity. Under these conditions, those with more prior entrepreneurial experience are likely to be better able to discover more valuable opportunities in the market, and will have developed skills to help them exploit these opportunities (Delmar & Shane, 2006; Shane, 2003; Shane & Venkataraman, 2000).

For entrepreneurs exploiting more novel opportunities, little information exists to help the entrepreneur make decisions, as their opportunities are more innovative and unique (Dequech, 1999, 2003; Dunn, 2001; Knight, 1921). For an entrepreneur to succeed under these conditions, researchers suggest that prior entrepreneurial experience is also key, as only by going through the enactment process can individuals learn to operate under these conditions. For example, prior start-up experience helps the entrepreneur to learn how to operate under more uncertain conditions by building up different types of cognitive tools, such as the ability and willingness to generalize from small samples (Alvarez & Barney, 2007; Baron, 1998; Busenitz & Barney, 1997; Westhead et al., 2009). Further, entrepreneurial experience could also develop other decision-making heuristics that can help them operate with limited external information (Alvarez & Barney, 2007; Busenitz & Barney, 1997; Debrulle, Maes, & Sels, 2013; McMullen & Shepherd, 2006). This research suggests that entrepreneurs with more prior start-up experience can use the heuristics and biases developed during their prior entrepreneurial experience to improve performance, especially under more innovative, novel conditions

Since theory suggests the importance of prior entrepreneurial experience, many researchers have focused on the key differences between experienced and novice entrepreneurs. One important difference between these entrepreneurs is the way that entrepreneurial experience changes the way individuals think. For example, Busenitz and Barney (1997) found that entrepreneurs were more likely to use heuristics in their thinking than managers in traditional firms (who had no prior entrepreneurial experience). Entrepreneurs were seen as being more overconfident in their abilities and more likely to generalize from small samples, called the representativeness bias (Busenitz & Barney, 1997; Tversky & Kahneman, 1974, 1981). These heuristics were argued to allow the entrepreneur to be able to better make decisions in situations with little outside information. Further, Westhead and colleagues (2009) found that serial entrepreneurs were more likely to use heuristic thinking, while novice entrepreneurs (much like managers in traditional firms), were more likely to use systematic thinking. More recently, Dew and colleagues (2009) conducted experiments to examine how novice entrepreneurs (MBA students) thought through opportunity exploitations versus how more experienced entrepreneurs thought through this process. Asking participants to examine the same opportunity, they found that MBA students were more likely to use analogical thinking, common strategy tools ('textbook thinking'), and were more accepting of market research than expert entrepreneurs. Experts were more likely to think holistically, draw on personal experience, think beyond the given research, and think about effective partnerships. One important outcome of this line of research is that experienced entrepreneurs discover more opportunities, more innovative opportunities, and opportunities with more value creating potential (Dew et al., 2009; Ucbasaran, Westhead, & Wright, 2009). However, this research largely left unanswered questions on the performance differences between novice and experienced entrepreneurs, although this research does suggest that entrepreneurial experience should improve performance.

Empirical research, largely based in entrepreneurial human capital literature, has examined the role of prior entrepreneurial experience in the performance of an entrepreneur's current venture. They have largely found prior entrepreneurial experience positively impacts performance, lending support to the theoretical arguments. The more prior start-ups an entrepreneur has been involved with, the more entrepreneurial human capital they develop, which helps them build knowledge and skills to discover, create, and exploit opportunities (Westhead et al., 2009). Prior start-up experience is seen as giving an entrepreneur skills associated with starting a firm, such as obtaining funding, business planning, and market building (Bruderl et al., 1992). In research on manufacturing firms, Chandler and Hanks (1994) found that entrepreneurial competence was linked to increased performance. Bosma and colleagues (2004) found that individual with more start-up experience earned more profits than those with no prior start-up experience. Further, Delmar and Shane (2006) found that more team start-up experience increased venture survival. Parker (2013) found that success in the prior start-up improved performance on the current venture. In their meta-analysis, Unger and colleagues (2011) call industry and entrepreneurial-specific human capital task-specific human capital because they argue that these experiences are directly related to work in new ventures, and find that task-specific human capital has a stronger effect on performance than general human capital investments (such as education). Overall, this research suggests that investments in experienced entrepreneurs will perform better in their current ventures than in novice entrepreneurs.

However, recent research has called these earlier findings into question. West and Noel (2009) found that prior start-up experience also had no impact of new venture performance. Hmieleski and colleagues (2015) found that prior-start up experience did not lead to improved performance. Specifically, they found that prior start-up experience had no relationship with performance under low environmental dynamism, and actually harmed performance under higher levels of environmental dynamism. What can explain the disparities in these studies with early studies? One potential moderating factor is that all prior studies simply examined the direct effect of prior start-up experience, and did not study the effect that prior start-up experience has through its impact on the effectiveness of entrepreneurial actions. Recent research has argued that entrepreneurial absorptive capacity, the ability of an entrepreneur to learn from external information, differs for novice and experience entrepreneurs (Debrulle et al., 2013), and therefore, different actions could have different impacts on performance for experienced entrepreneurs versus novice entrepreneurs.

Entrepreneurial Actions

A variety of entrepreneurial actions have been noted in the literature (Bird, Schjoedt, & Baum, 2012; Klein, 2008; McMullen & Shepherd, 2006). This paper focuses on two specific actions: environmental scanning (Beal, 2000; Fiet & Patel, 2008; Peters & Brush, 1996; Shepherd & DeTienne, 2005; Stewart, May, & Kalia, 2007) and prototype testing (Blank & Dorf, 2012; Brown, 2008; Kelley, 2001; Pisano, 1996; Ries, 2011).

Environmental scanning. Environmental scanning involves searching the environment for information related to potential competitors, potential demand, and how to market the opportunity to customers. Scanning the environment can help the entrepreneur acquire, make sense of, and act on preexisting information. These actions can help entrepreneurs: a) spot missing information and conduct thought experiments without first expending resources, b) match the supply and demand of resources to avoid time consuming bottlenecks, and c) pursue goals in a systematic way through the development of concrete action steps (Delmar & Shane, 2003; Gruber, 2007). Scanning the environment can also help the entrepreneur align their strategies with the environment, improving their performance (Beal, 2000).

Prototype testing. Prototype testing is the creation of opportunity-specific information, by a trial-and-error, experimental learning process (Blank & Dorf, 2012; Kelley, 2001; Pisano, 1996; Ries, 2011). Prototype testing can help entrepreneurs generate information by asking the right questions, designing new experiments, thinking creatively, and remaining flexible (Alvarez & Barney, 2007; Mintzberg, 1994). As Brown argued, "The goal of prototyping isn't to finish. It is to learn about the strengths and weaknesses of the idea and to identify new directions that further prototypes might take" (2008, p. 3).

While there is scant amount of empirical research examining prototype testing in entrepreneurship, there has been some research done in the organization and product innovation literature. For example, there is anecdotal evidence that increased prototype testing improves product innovation (Brown, 2008; Kelley, 2001). Organization scholars have also examined the role of preproduction experience, said to be a "low-risk learning, especially by trial and error" (Carroll, Bigelow, Seidel, & Tsai, 1996, p. 120). In the early automobile industry, researchers found that this experience decreased an organization's mortality rate (Carroll et al., 1996). Other researchers found that pre-founding experience was also an important factor in the quality of Israeli wine producers' products (Simons & Roberts, 2008). Finally, at the industry level, Moeen and Agrawal (Moeen & Agarwal, 2015) show that during an industry's technological incubation period, all types of firms invest in experiments, and even those that fail increase the knowledge of industry incumbents. Preproduction experience is much like individuals testing prototypes, where individuals (or teams of individuals within organizations) can learn from the market, for both successful and failed tests (Kelley, 2001). Taken together, this research suggests that early experimentation and prototype testing can help the organization (or individual) achieve future success.

Action effectiveness. The effectiveness of these different actions may depend on whether the entrepreneur is a more novel or a less novel opportunity (Alvarez & Barney, 2007; Shane, 2003). When an entrepreneur is exploiting a less novel opportunity, he or she is largely imitating other opportunities in the market, and therefore information about the value-creating potential of the opportunity is available. The entrepreneur can examine other, similar opportunities to gather information on the competition, how the competitors market their opportunity, and the demand for those similar products or services. This allows the entrepreneur to better calculate the potential of their opportunity.

However, when an entrepreneur is exploiting more novel opportunities, they are more innovative, unique, and different from other opportunities in the market. Under this condition, less information exists for the entrepreneur to use to decide their actions, and they are more likely to need to create new information in order to succeed. While less information exists about these opportunities, some information almost always does exist. For example, for entrepreneurs creating a novel mobile application, information about how to program in a given language and how to upload an application to the market is readily available for the entrepreneurs to gather and learn from. However, information about the market or features to include might not be known, or even knowable, before the entrepreneurs start to create their software and show it to potential customers. These potential customers might not understand the application until they are able to see an early version (Kelley, 2001). This is why the creation of information specific to the opportunity is suggested to be so important—it helps the entrepreneur transform their initial beliefs about an opportunity into one more valuable in the market (Alvarez & Barney, 2007).

Experience and Actions for Less Novel Opportunities

For less novel, more imitative opportunities, information about a specific opportunity exists, because the new venture is related to other ventures in such a way that an entrepreneur is able to at least calculate the probabilities of different outcomes (Alvarez & Barney, 2007; Knight, 1921; Shane & Venkataraman, 2000). Since novice entrepreneurs engage in more systematic thinking (Westhead et al., 2005), more time spent searching the environment for information should improve performance. Having more information should help the novice entrepreneur be better able to refine his or her calculations. This information can also help the entrepreneur understand the needs of customers and how competitors are likely to respond. However, there is a limit to this benefit. Too much time spent scanning the environment will likely begin to hurt performance. Individuals have limits to the amount of information they can process, and further increasing the amount of information is likely to lead to cognitive overload and lower overall performance (Baron, 1998; March & Simon, 1958; Simon, 1990; Simon, Houghton, & Aquino, 2000). Also, spending too much time takes away from other valuable actions, and could lead the novice entrepreneur not to get their idea to market fast enough. This leads to diminishing returns to increased environmental scanning. As entrepreneurial experience increases, the relationship between environmental scanning and performance differs. These entrepreneurs are more likely to engage in heuristic thinking (Baron, 1998; Busenitz & Barney, 1997; Westhead et al., 2005). This should lead them to gain more from less time spent scanning the environment, because they already have some knowledge of the environment, and they can more quickly learn from outside information (Dew et al., 2009). However, these entrepreneurs are also likely to make more mistakes than novice entrepreneurs, who are more systematic in their search, and therefore continued scanning beyond some threshold by experience entrepreneurs is likely to more quickly reduce performance. Therefore we hypothesize the following:

- H1a*: For novice entrepreneurs, time spent scanning the environment will have an inverse-U relationship with performance under conditions of risk.*
- H1b*: Increases in prior entrepreneurial experience will moderate the inverse-U shaped relationship between time spent scanning the environment and performance under conditions of risk, such that the peak amount of environmental scanning will be shifted to a lower level and the performance will decrease more rapidly after the peak.*

Prototype testing requires the entrepreneur to spend time testing different versions of their product with different individuals, creating opportunity-specific knowledge from a small subset of the market. This trial-and-error learning requires the individual to generalize from a set of small samples, a heuristic that novice entrepreneurs are not as adept at using as serial entrepreneurs (Busenitz & Barney, 1997; Westhead et al., 2009). The systematic thinking of novice entrepreneurs means they are more likely than experienced entrepreneurs to make mistakes in generalizations that reduce performance, as they lack the experience in these types of generalizations. Novice entrepreneurs might begin to modify and change their ideas too much—over pivoting in an effort to match what the market desires, which could lead to not matching what the market really is looking for. However, more experienced entrepreneurs are better at using heuristics and have experience in generalizing from little information. Experienced entrepreneurs should benefit from more prototype testing. Gathering more diverse knowledge through prototype testing can help experienced entrepreneurs by leading them to ask the right questions, design new experiments, think more creatively, and remain flexible (Alvarez & Barney, 2007; Mintzberg, 1994) throughout the exploitation process.

- H2a*: For novice entrepreneurs, higher levels of prototype testing will reduce performance under conditions of risk.*
- H2b*: Increases in prior entrepreneurial experience will positively moderate the relationship between prototype testing and performance under conditions of risk, such that more prototype testing will lead to improved performance for more experienced entrepreneurs*

Experience and Actions for More Novel Opportunities

For more novel, unique and innovative opportunities, there is less information in the environment on which to base decisions. The knowledge gained by working in a given industry or in a given job might not create a base of related knowledge, since novel opportunities are less like others on the market (Alvarez & Barney, 2007; Alvarez et al., 2013; Knight, 1921). While some information exists, it is likely not related to the specific opportunity being exploited, since there are no current customers or few competitors in which to base judgments. By systematically searching the environment under these conditions, novice entrepreneurs are likely collecting more data that is not relevant to their opportunity, and thus will not learn about the potential of their specific opportunity. In fact, collecting more data will actually harm performance, as it will lock in the novice entrepreneur into believing that the knowledge is more relevant than it truly is. However, those with more prior start-up experience will be better able to judge the environment in which they are acting. This will give these entrepreneurs the ability to scan the environment and actually learn something, even when little information exists. Experienced entrepreneurs are likely to be able to generalize from what information exists. However, there is still a limit to the usefulness of environmental scanning, due to cognitive constraints within the individual (Baron, 2008; Dunn, 2001; March & Simon, 1958). Further, there is a trade-off in actions; more time spent scanning the environment is less time spent performing other beneficial actions such as prototype testing. This leads to diminishing returns for the entrepreneur as they increasingly scan the environment. Therefore, we hypothesize the following:

- H3a*: Environmental scanning will have a negative relationship with performance under conditions of uncertainty*
- H3b*: Prior start-up will positively moderate the relationship between environmental scanning and performance under conditions of uncertainty, such that increases in environmental scanning will have an inverse-U shaped relationship with performance*

Prototype testing will improve performance for more novel opportunities for all entrepreneurs. Under highly novel, unique, and innovative conditions, little outside information exists. Therefore, to learn about their opportunity, entrepreneurs must test their ideas with the market. "As entrepreneurs act upon their initial beliefs about opportunities and then observe the market responses, beliefs are transformed, reflecting the acquisition and creation of knowledge and information" (Alvarez & Barney, 2007, p. 15). By repeatedly testing their ideas, entrepreneurs can gain more information about the potential of their idea, since they would be accessing more unique knowledge sets (Ries, 2011). Therefore, increased prototype testing should greatly improve performance for novel opportunities. Further, increases in prior start-up experience will actually lead to even better performance. Prior start-up experiences give entrepreneurs the ability to understand how to build and create a market, and be able to operate under more uncertain conditions (Alvarez & Barney, 2007; Alvarez et al., 2013). Therefore, we hypothesize the following:

- H4a*: Higher levels of prototype testing will improve performance under conditions of uncertainty*
- H4b*: Prior start-up experience will positively moderate the relationship between prototyping and performance under conditions of uncertainty*

Empirical Setting

To test the hypotheses, we turn to entrepreneurs who create apps (applications) for the Google Play™ store. We collected data on the developers of all apps listed as 'Top New Apps' in the Google Play™ store on June 10, 2015. For each app, we captured the developer's email address, and sent out a survey instrument to capture data about the entrepreneur's human capital investments and actions they took prior to launching their app. The survey was designed to capture information on a variety of human capital investments and the actions they took to develop their app. We further capture information on the individual's organization. We ask if the entrepreneur is considered an owner, the size of the development team, the size of the organization, the type of firm (whether or not the firm is a legal entity), whether the individual works full-time or part-time, and the number of apps developed by the firm. We also capture data on the financing of the app.

Overall, we sent out 9100 surveys and received 789 responses, for a response rate of 8.7%. Nonrespondents had similar performance with respondents, so we do not believe our sample is biased. For this study, we chose to focus on a specific type of organization—one with only one member. This is an important subset of entrepreneurs, as the U.S. Census Bureau found that, in 2013, over 23 million people in the U.S. are classified as working in this type of organization, and these individuals generated over $1.1 trillion in revenue.[14] Further, we chose to examine individual entrepreneurs because the survey only captured human capital data on the respondent. If the respondent worked in a larger team, then the unobservable human capital attributes of the team could bias the results. A developer was considered an individual entrepreneur if they indicated that they were the owner/founder of the development organization, and the organization had only one member. These organizations do not need to be formal legal entities to be included. This led to a final sample size of 366 individual entrepreneurs.

Measures

Dependent variable. The dependent variable in these analysis is a measure of entrepreneurial performance. For app developers, we chose to use the number of installs the app receives in the Google Play™ store. We collected data each week for approximately 8 months (33 weeks) after we surveyed the entrepreneurs. We chose to focus on installs because this allows us to examine entrepreneurs who choose to develop and promote free applications, who would be missing if we looked solely at financial performance (Rindova et al., 2009). Google gives a categorical range of installs rather

[14] http://www.bizjournals.com/prnewswire/press_releases/2015/05/27/DC18217

than the actual number, and therefore, our dependent variable is an ordered-category of installs. We then coded these into 5 categories: 0 installs, 1-9 installs, 10-99 installs, 100-999 installs, and 1000+ installs. These were then coded 0-4, and these were used in the models to ease interpretation. Using this categorization scheme, approximately 60% of apps received less than 1000 installs during our time period. Using the actual category does not substantively change the results.

Independent variables. Our survey was designed to collect data on two distinct entrepreneurial actions. First, we asked each entrepreneur how many prototype versions they tested prior to launching their app. We chose this measure since an increase in prototypes tested shows the entrepreneur is attempting to learn from newly created information. This measure varied from 0-30. Next, we assessed the amount of time spent scanning the environment, searching for three types of market information: competitor analysis, demand analysis, and analyzing how to market your app. We then summed the minimum time spent searching in each category. This varied from 0-303 hours. We chose a time measure because more time spent searching should allow the entrepreneur to gather more information. This variable was mean-centered in the analysis to ease interpretation and reduce any possible multicollinearity. Finally, we used the survey to assess whether or not the individual was an owner or co-owner of a previous start-up. Following previous literature (Hmieleski et al., 2015), we measured this as the number of prior start-ups the entrepreneur had owned or co-owned.

Opportunity novelty. To determine the novelty of the opportunity the entrepreneur was exploiting, we utilized a unique, opportunity-specific measure of the level of similarity between different apps. The less similar an app is to other apps on the market, the more novel and unique the app. This was an improvement over industry-based measures (for examples, see: Dencker & Gruber, 2015; Hmieleski et al., 2015), since different opportunities within the same industry could be different (Raffiee & Feng, 2014). Our measure used text-based analysis to of the description of each app, and compared it to all other apps in the marketplace a month before the app was launched. We then calculated the similarity between all apps in the dataset. For our measure, we used the 10 nearest neighbors (the 10 apps closest in description of the focal app), and averaged the level of similarity of these 10 apps. This ranged from .008 to .89, with a higher score meaning the 10 nearest neighbors were more similar. While we included the continuous variable as a control, to ease interpretation, we split the sample at the mean and ran low novelty and high novelty models separately. The mean level of similarity was .15, meaning that similarity score less than .15 were coded as highly novel, while those greater than .15 were coded as less novel.

Control variables. This analysis utilized several control variables that are linked to the number of installs an app receives. First, researchers have shown that entrepreneurs with greater access to resources perform better than those with less access to resources, so we controlled for the level of financing the entrepreneur received to develop their app. Developing apps for the Google Play™ store is less resource intensive than many other entrepreneurial endeavors. At minimum, it requires a computer, and individual programmer, and an Internet connection. The most needed resource for these developers is capital, needed to fund development, marketing efforts, and human capital. The survey instrument asked the entrepreneurs how much funding they acquired for their app. The categories were: friends and family, crowd funding, bank financing, venture capital, personal savings, credit cards, and money from other businesses. The entrepreneur could select multiple options. We summed the total amount of financing and included this as a control.

Second, we used three other survey measures to control for the human capital of the entrepreneur (Dencker & Gruber, 2015; Hmieleski et al., 2015; Unger et al., 2011). The first measure was another measure of related human capital, the number of prior apps the entrepreneur had developed. The second of these was years of education (standardized to ease interpretation). The third was years of managerial experience.

We also included several binary indicators for app features, including if the app was a paid app or a free, and whether the app offered in-app purchases. We also controlled for the country of origin as a dummy variable indicating if the entrepreneur was in the U.S. We controlled for the time the application has been on the market (in days), as longer availability could increase the number of installs. Finally, we included a binary control for the games category, as these apps could have a broader audience, leading to more downloads.

Following previous literature, we also controlled for the entrepreneur's motivation. The survey asked entrepreneurs the importance of getting the highest number of installs possible. We included this as a binary dummy variable which equals '1' if the entrepreneur indicated this was important to them. We also controlled for whether or not the entrepreneur worked full time for the current app development organization. Individuals who worked full time, or wanted to work full-time, were coded with a binary '1,' while those who worked part-time and wished to remain part-time, were coded with a '0'. We tested several different variants of this measure, and found all to be substantively the same.

Methods

To test our hypotheses, we use ordered-logistic regression, since our dependent variable is ordered categories (Wooldridge, 2010). We utilized robust standard errors to control across-app heterogeneity (Huber, 1967; White, 1980). We also included wave (time) fixed-effects.

Results

Summary statistics are shown in Table 4.1. The correlations act in the expected ways. Interestingly, as expected, the amount of financing had only a small correlation with performance. This helps to remove a major alternative explanation for increased performance; those with more resources, or more access to resources will perform better. We also tested for multicollinearity using standard regressions and variance inflation factor (VIF) testing. Results show that all variance inflation factors were well under 10, indicating that we have no issued from multicollinearity.

Table 4.2 shows the resulting ordered logistic regression models for risky apps. Model 1 is the control model, with controls acting in the expected way. Interestingly, apps from developers in the U.S. perform significantly worse than apps from developers not in the U.S. Model 2 adds the direct effects of prototype testing, environmental scanning time, and prior start-up experience. Model 3 adds the interactions between prior start-up experience and the entrepreneurial actions. Model 3 shows that for novice entrepreneurs, environmental scanning has a significant positive main effect, with a negative, and significant second-order term. This indicates that there is an inverse-U shaped relationship between environmental scanning and performance for novice entrepreneurs acting under risky conditions, lending support for H1a. As an entrepreneur has increasing prior start-up experience, we see both the main effect and the second-order term in the interactions are both negative and significant. This indicates that the peak value of environmental scanning for experienced entrepreneurs is shifted to the left, to a lower amount of time spent scanning, yet after the peak the performance will drop off faster for experienced entrepreneurs versus novice entrepreneurs. Therefore, we find support for H1b. Prototype testing has a significant negative effect on performance for novice entrepreneurs acting under conditions of risk. This supports H2a. However, prior entrepreneurial experience does not appear to moderate this relationship, as the interaction term is positive, but not statistically significant, indicating that experienced entrepreneurs perform worse with more prototype testing. Therefore, we find no support for H2b.

Table 4.3 shows the results for entrepreneurs acting under conditions of uncertainty. Model 1 is the control model, while Model 2 adds the main effects of environmental scanning, prototype testing and prior start-ups. Model 3 adds the interactions between entrepreneurial action and prior entrepreneurial experience. The effect of environmental scanning for those with no prior start-ups shows an inverse-U relationship, with a positive and significant main effect, and a negative and significant second-order term. This is opposite to our predictions of a negative relationship, so H3a is not supported. However, for experience entrepreneurs, we see the main interaction effect is positive and significant, with no significance for the second-order term. This provides support of the inverse-U relationship predicted in H3b. Prototype testing has no effect for novice entrepreneurs under conditions of uncertainty, lending no support for H4a. However, as prior start-up experience increases, prototype testing is shown to have a positive and significant effect. This provides support for H4b.

To better understand our results, we use marginal analysis to predict the probability that an app gets 1000 or more installs. Figure 4.1 shows the time spent scanning the environment versus performance for various numbers of prior start-ups under less novel conditions, with all other controls held at their mean. As shown, a novice entrepreneur's probability of achieving 1000 or more installs rises initially, but begins to fall off after approximately one standard deviation above the mean of environmental scanning (approximately 48 hours scanning the environment), and shows that above this, scanning more actually begins to hurt the chances of 1000 or more installs. As experience rises from 0 prior start-ups to 2 prior start-ups, we see this peak shift to the left, to about the average time spent scanning (about 16 hours). After this, the relationship falls off more quickly than for novices, indicating that more time spent scanning is hurting performance.

Figure 4.2 shows the number of individuals that the entrepreneur tested prototypes with versus performance for various levels of prior start-up experience for less novel apps and more imitative conditions, with everything else set to the mean value. As shown, for all entrepreneurs, as the number of prototypes increases, the performance drops, significantly reducing the probability of achieving 1000 or more installs. Novice entrepreneurs have around a 38.9% of getting 1000 or more installs with no prototype testing, and this drops to a 24.8% chance when they test 15 prototypes. For entrepreneurs with two prior start-ups, the pattern is the same. When not testing prototypes, these entrepreneurs only have a 37.6% chance of getting 1000 or more installs, and this drops to 27.2% when they test 15 prototypes. This shows that prototype testing is not an effective action for less novel opportunities for any entrepreneur.

Figure 4.3 shows time spent scanning the environment versus performance for 0, one, and two prior start-ups under more uncertain conditions, with all other controls held at their mean value. At the average amount of time scanning the environment, the results show that both novice and serial entrepreneurs have between a 26% and 27% chance of getting 1000 or more installs. However, experienced entrepreneurs gain more for more time spent scanning. At two standard deviations above the mean amount of scanning (about 80 hours), entrepreneurs with two prior start-ups have a 48.9% chance of getting 1000 or more installs, while novice entrepreneurs now only have a 37.9% chance of getting this many installs. This shows that, under more novel and innovative conditions where little information exists, experienced entrepreneurs are better able to gain an advantage from examining the environment than novice entrepreneurs. It is also evident from the figure of diminishing returns to increased environmental scanning, as the increase from one to two standard deviations is smaller than the increase from the average to one standard deviation.

Figure 4.4 shows the number of prototypes the entrepreneur tested versus performance for 0, one, and two prior start-ups under more novel conditions, with everything else set to its mean. When no prototypes are tested, the graph shows that entrepreneurs with two prior start-ups only have a 20.7% chance of getting 1000 or more installs, while novice entrepreneurs have a 25.3% chance of achieving this level of installs. However, when the experienced entrepreneur (with two prior start-ups) tests 15 prototypes, this dramatically changes. Now the entrepreneurs with two prior start-ups have a 42.2% chance of achieving 1000 or more installs, while novice entrepreneurs have a 27.8% chance of getting this many installs. This shows that, under more innovative conditions, prototype testing is essential for more experienced entrepreneurs, but does not have the same benefits for less experienced entrepreneurs.

Additional Tests

To further explore our findings and to further establish the validity of our results, we ran several additional tests. First, we tested two an alternative dependent variables. The first of these was the full categorization scheme, and found substantively the same results as the models we present. We also tested a binary variable indicating 1000 or more installs. These results were also consistent with our main models, and are available from the authors upon request.

We also wanted to further explore our findings on prototyping, as our finding that prototyping did not add value for less novel apps was surprising. One possible explanation is that it is possible that individuals use environmental scanning to improve their ability to prototype effectively—they search the environment for features to include, and test that with potential customers. Therefore, we ran tests with an interaction between environmental scanning and prototype testing, with the results presented in Table 4.4. Controls were included, but not shown to conserve space. Model 1 shows the results for less novel apps. We found that, indeed, increased environmental scanning leads to better value created through prototyping. This results suggests that for prototyping to be effective under less novel conditions, environmental scanning must be done as well. Model 2 shows the results for more novel apps. Results showed this interaction not to be statistically significant. This indicated that individuals' environmental scanning is not improving (or even impacting) an individual entrepreneur's ability to prototype under more novel conditions.

Discussion and Conclusion

This study looked to develop a deeper understanding of the performance implications of entrepreneurial actions by novice and experienced entrepreneurs. This paper argued that environmental scanning and prototype testing have different effects for novice and experienced entrepreneurs for more and less novel opportunities. Specifically, we find that for novice entrepreneurs exploiting less novel, imitative opportunities, environmental scanning has an inverse-U shaped relationship with performance, while for experienced entrepreneurs, the relationship gets dampened, showing that the peak amount of time scanning the environment is lower and performance falls off faster above this peak. For these types of opportunities, prototype testing has a negative effect on performance for all entrepreneurs. For more novel, unique, and innovative opportunities, we find that environmental scanning still has an inverse-U shaped relationship for all entrepreneurs, but increases in environmental scanning help experienced entrepreneurs more than novice entrepreneurs. Further, under these conditions, we find that prototype testing has no effect for novice entrepreneurs, but it greatly increases the performance of experience entrepreneurs.

Novice entrepreneurs have no experience in entrepreneurship. We find that, for all types of apps, increases in environmental scanning improves the performance of these entrepreneurs, although there are diminishing returns to increased scanning beyond a certain threshold. The systematic and analytic 'textbook' thinking of these entrepreneurs allows them to make sense of external information to improve performance. However, too much time spent searching for information will eventually lead to lower performance, since more time searching means less time spent performing other effective actions, and more time to get ideas to the market. It is interesting that this relationship holds for more novel apps, where less external information exists. However, scanning the environment for potential competitors, customers, and how other entrepreneurs market their opportunity is still important. For novice entrepreneurs, at least spending some time systematically looking for this information can provide benefits in terms of a better idea about the competition and how to position their products against others in the market.

We find that the more novice entrepreneurs test prototypes for less novel apps, the worse they perform. Novice entrepreneurs have not developed the skills to easily generalize from small samples, and are much more likely to systematically analyze the information they receive (Busenitz & Barney, 1997; Westhead et al., 2005). This suggests they are likely to try and pivot under each prototype tested (Ries, 2011), changing their apps to meet what they feel the market is looking for based on the responses gathered from their prototypes. This could lead to over pivoting, moving them away from what the market actually wants in their app into something else that does not meet as many needs for all of their potential customers. For more novel apps, we find no significant relationship between prototype testing and performance for novice entrepreneurs. Since there is less outside information available, some novice entrepreneurs could be over-pivoting, while some could be under-pivoting. Overall, we find that prototype testing is not an effective action for novice entrepreneurs, although practice at prototype testing could help novice entrepreneurs in subsequent ventures. They could learn how to prototype test, with benefits coming to them as they are better at prototype testing in their newer ventures. This is an area for future research.

Experienced entrepreneurs have prior experience as an owner or co-owner of an entrepreneurial venture. These entrepreneurs have dealt with operating in entrepreneurial environments. When experienced entrepreneurs create less novel, more imitative apps, we find that scanning the environment for a shorter time (than for novice entrepreneurs) is better for performance. For these entrepreneurs, the more prior knowledge they possess (Shane, 2000; Shane & Venkataraman, 2000), coupled with their use of heuristic thinking, could help them to learn what they need to succeed faster than novice entrepreneurs. However, if they continue to search, this could lead them to search for more confirmatory information, which does not necessarily improve performance (Busenitz & Barney, 1997; Westhead et al., 2009). For more novel apps, we find a similar relationship, such that more time spent scanning the environment also has an inverse-U shaped relationship with performance. For these apps, the heuristic thinking of experienced entrepreneurs may provide additional benefits to them, as they do not spend too much time over-analyzing information that may or may not be relevant to their opportunity.

Prototype testing has a different effect for experienced entrepreneurs creating less novel apps. The more prototypes they test, the lower they perform. Since information exists about similar apps in the market, and the more experienced entrepreneur is likely to know more about this type of environment (e.g., its competitors and dynamic) than a novice entrepreneur. However, more experienced entrepreneurs are also more overconfident (Busenitz & Barney, 1997; Westhead et al., 2005), and this could be causing them to ignore information they receive from prototype testing unless it confirms their prior beliefs. This could be causing them to under-pivot (Ries, 2011), leading to reduced performance, as they are not meeting the needs of their customers. However, when creating more novel apps, prototype testing greatly improves the performance. By testing more prototypes, experienced entrepreneurs can get feedback from more diverse knowledge sets, which can help them overcome their overconfidence and hubris, since they realize that they do not know as much about these types of environments. Having gone through the enactment process before has given experienced entrepreneurs the ability to generalize from small samples, and have tacit knowledge of how to operate in uncertain environments (Alvarez & Barney, 2007). Overall, we find that prototype testing is an effective action for experienced entrepreneurs when they are creating more novel apps, and is not effective if they are creating less novel apps.

This paper makes several contributions to the literature. First, we add the growing literature on experienced versus novice entrepreneurs (Busenitz & Barney, 1997; Ucbasaran et al., 2009; Westhead et al., 2005, 2009), by showing how different actions have different benefits for each type of entrepreneur. Prior literature has shown that experienced entrepreneurs think differently than novice entrepreneurs, and take different actions with searching for opportunities (Westhead et al., 2005). We go beyond this by examining the actions entrepreneurs take while exploiting an opportunity. We find that environmental scanning has an inverse-U shaped relationship for all entrepreneurs for all types of opportunities. However, for less novel opportunities, increased environmental scanning is more helpful for novice entrepreneurs, while more experienced entrepreneurs do not need to search as much. For more novel opportunities, this changes, where increased searching provides more benefits to experienced entrepreneurs. We also show that prototype testing hurts performance for all entrepreneurs exploiting less novel opportunities, but is extremely effective for experienced entrepreneurs creating more novel and innovative opportunities.

Second, we add to the literature on entrepreneurial action (Blank & Dorf, 2012; McMullen & Shepherd, 2006; Ries, 2011), by showing that different actions have different performance effects for different types of opportunities for different types of entrepreneurs. By examining the process of entrepreneurial exploitation, we can gain a better understanding of what it takes for different types of entrepreneurs to be successful at exploiting different types of opportunities. We find that both environmental scanning and prototype testing can both be effective actions, but this relationship depends on two things: the prior experience of the entrepreneur and the level of novelty of their opportunity. Novice entrepreneurs perform better when exploiting less novel opportunities engaging in moderate levels of environmental scanning and less prototype testing. For more novel opportunities, these entrepreneurs should scan the environment more and prototype less. We find that experienced entrepreneurs perform better for less novel opportunities by scanning the environment more and prototyping less. When exploiting more novel opportunities, both moderate levels of environmental scanning and increased prototype testing lead to improved performance. While many popular press books (Ries, 2011) argue that all entrepreneurs should engage in more prototype testing and pivoting to improve their chances at success, our research shows that this is only the case for experienced entrepreneurs exploiting more novel opportunities.

Finally, we add to the recent conversation on creation versus discovery theories of entrepreneurship. One of the key differences in these theories is that the nature of opportunities differs across contexts. While discovery theory argues that entrepreneurs discover opportunities under conditions of risk (less novel, more imitative opportunities), the creation theory of entrepreneurship argues that entrepreneurs create opportunities through their actions under conditions of Knightian uncertainty, leading to more novel, unique, and innovative opportunities (Alvarez & Barney, 2007; Alvarez et al., 2013; Knight, 1921; Shane & Venkataraman, 2000). While some researchers have recently begun to examine the level of uncertainty at the industry level (Hmieleski et al., 2015), our study goes beyond this to examine whether *a specific opportunity* is more or less novel (Raffiee & Feng, 2014), and how the actions of novice and experienced entrepreneurs have different performance impacts for different types of opportunities. Overall, our results indicate that the opportunity-specific level of uncertainty is an important factor in understanding entrepreneurial performance (Raffiee & Feng, 2014), and that both risk and uncertainty can occur within the same industry. Overall, whether the entrepreneur is acting under risky or uncertain conditions makes a huge difference on how effective different actions can be, and how this relationship varies for both experienced and novice entrepreneurs.

There are several limitations to this study. First, we do not know the types of prior ventures for our entrepreneurs, or the information conditions under which they operated. It could be the case that they have experience imitating other opportunities, which might not give them the skills needed to overcome their biases under more uncertain conditions. Future research could better understand the nature of the conditions under which prior entrepreneurs gain experience and how they relate to current opportunities. Second, we also do not know the success of the entrepreneur's prior ventures. Research shows that prior success can help build future success (Parker, 2013), so it would be fruitful to examine whether success or failure under uncertain conditions leads to better learning outcomes for the future. Finally, we tested our hypotheses with a survey of Google Play app developers, an environment that does not require a large amount of resources to be successful. Other entrepreneurs act in resource constrained environments (Baker & Nelson, 2005; Sarasvathy, 2001), and the prior start-up experience could impact the performance here by allowing more access to resources (Brush, Greene, & Hart, 2001) or increase the ability to enroll stakeholders (Burns et al., 2015). It would be fruitful to replicate our study in other contexts to examine how resource constraints affect our results.

This research has important implications for actual entrepreneurs, and entrepreneurship education. For both novice and experienced entrepreneurs, our results point to different actions that they can take to improve performance while exploiting more or less novel opportunities. Therefore, entrepreneurs can select actions that can best help them under the conditions in which they operate. For entrepreneurship education, this study shows that simply teaching all entrepreneurs to either only scan the environment (in part to write business plans), or to only prototype test, misses important aspects of these relationships. Educators must alert students to the differences between different types of opportunities, and help individuals choose the most effective actions under the conditions in which they operate.

The results of this study point to several fruitful avenues of future research. First, researchers can begin to further examine the opportunity-specific information conditions under which entrepreneurs operate. Even within a dynamic industry, some entrepreneurs can be exploiting less novel opportunities under conditions of risk, while some can be exploiting more novel opportunities under more uncertain conditions. Further examining this in different industries can help us better explain the variance in performance within a given industry. Further, researchers can examine other actions that entrepreneurs take to exploit their opportunities, such as business planning. By revisiting prior work on business planning, we might find some instances where planning is extremely important, and others where planning actually harms entrepreneurs, and what type of entrepreneurs business planning helps the most.

In conclusion, we found that for novice entrepreneurs exploiting less novel opportunities, environmental scanning improves performance (up to some threshold), while prototype testing actually reduces performance. For experienced entrepreneurs, we found that scanning the environment also improves performance, but the peak amount of scanning is lower for these entrepreneurs, and performance falls off more quickly after the peak. We find that prototype testing is not effective for more experienced entrepreneurs exploiting less novel opportunities. For more novel opportunities, we found that novice entrepreneurs do not improve performances by prototype testing, but more time spent scanning the environment does increase performance. For more experienced entrepreneurs exploiting more novel and innovative opportunities under uncertain conditions, we found that environmental scanning improves performance more than it does for novices, but also at a diminishing rate. We found that prototype testing is extremely effective for experienced entrepreneurs exploiting more novel opportunities. Overall, our results point to the further differences between novice and experienced entrepreneurs, and that the actions taken by each have different performance implications for different types of opportunities.

Table 4.1

Summary Statistics for Mobile Application Developers

Variable	*N*	mean	*sd*	min	max
Install Category	**11472**	**3.04**	**0.89**	**1**	**4**
Prototypes	**11440**	**3.01**	**5.39**	**0**	**30**
Environmental Scanning Time	**11472**	**-0.29**	**0.55**	**-0.53**	**4.00**
Environmental Scanning Time ^2	**11472**	**0.39**	**1.15**	**0.01**	**15.97**
Prior # Start-Ups	**11472**	**0.76**	**1.73**	**0**	**20**
Prior # Apps Developed	**11472**	**4.77**	**6.97**	**0**	**30**
Education (years)	**11472**	**-0.16**	**1.06**	**-2.35**	**1.73**
Managerial Experience (years)	**11472**	**2.55**	**4.62**	**0**	**30**
Innovation Measure	**10701**	**0.16**	**0.09**	**0.01**	**0.89**
Financing Amount	**10703**	**364.33**	**2009.26**	**0**	**20100**
Paid	**11472**	**0.08**	**0.28**	**0**	**1**
Offers In-App Purchases	**11472**	**0.10**	**0.30**	**0**	**1**
Purpose	**11472**	**0.85**	**0.36**	**0**	**1**
Full Time	**11472**	**0.61**	**0.49**	**0**	**1**
Time on Market (days)	**11472**	**101.69**	**81.71**	**0**	**575**
Games	**11472**	**0.32**	**0.47**	**0**	**1**
Country==USA	**11472**	**0.29**	**0.46**	**0**	**1**
Wave	**11472**	**17.01**	**9.49**	**1**	**33**

Table 4.2

Ordered Logit Models for Install Category for Low Novelty

VARIABLES	Model 1	Model 2	Model 3
Prototypes Tested		**-0.030*****	**-0.044*****
		[0.008]	[0.009]
Environmental Scanning Time		**0.006*****	**0.015*****
		[0.002]	[0.002]
Env. Scanning Time Squared		**-0.000*****	**-0.000*****
		[0.000]	[0.000]
Prior # Start-Ups		**-0.056****	**-0.091*****
		[0.018]	[0.022]
Prior # Start-Ups X Prototypes			**0.006**
			[0.004]
Prior # Start-Ups X Env. Scanning			**-0.004*****
			[0.001]
Prior # Start-Ups X Env. Scanning Squared			**-0.000*****
			[0.000]
Prior # Apps Developed	**0.017*****	**0.021*****	**0.031*****
	[0.004]	[0.005]	[0.005]
Education	**-0.088****	**-0.089****	**-0.057+**
	[0.031]	[0.032]	[0.032]
Managerial Experience	**0.036*****	**0.047*****	**0.042*****
	[0.006]	[0.006]	[0.006]
Innovation Measure	**2.170*****	**2.229*****	**2.138*****
	[0.383]	[0.385]	[0.376]
Financing Amount	**-0.000***	**-0.000***	**-0.000+**
	[0.000]	[0.000]	[0.000]
Paid	**-2.874*****	**-2.883*****	**-2.950*****
	[0.104]	[0.112]	[0.116]
Offer In App Purchases	**0.134**	**0.176**	**0.078**
	[0.110]	[0.110]	[0.116]
Purpose	**0.452*****	**0.312****	**0.190+**
	[0.098]	[0.104]	[0.107]
Full Time	**-0.318*****	**-0.290*****	**-0.319*****
	[0.063]	[0.064]	[0.067]
Time on Market (days)	**-0.004*****	**-0.004*****	**-0.003*****
	[0.001]	[0.001]	[0.001]
Games Category	**0.257*****	**0.220****	**0.336*****
	[0.072]	[0.072]	[0.074]
Country=USA	**-1.338*****	**-1.420*****	**-1.422*****
	[0.076]	[0.079]	[0.079]
Wave Fixed Effects	**Included**	**Included**	**Included**
Observations	4,144	4,112	4,112
Log Likelihood	-4325	-4280	-4220
Pseudo R-Squared	0.159	0.163	0.175

Robust standard errors in brackets
**** p<0.001, ** p<0.01, * p<0.05, + p<0.1*

Table 4.3

Ordered Logit Models for Install Category for High Novelty

VARIABLES	Model 1	Model 2	Model 3
Prototypes Tested		**0.028*****	**0.009**
		[0.005]	[0.006]
Environmental Scanning Time		**0.011*****	**0.008*****
		[0.001]	[0.001]
Env. Scanning Time Squared		**-0.000*****	**-0.000*****
		[0.000]	[0.000]
Prior # Start-Ups		**-0.025**	**-0.057**
		[0.035]	[0.068]
Prior # Start-Ups X Prototypes			**0.030*****
			[0.005]
Prior # Start-Ups X Env. Scanning			**0.003****
			[0.001]
Prior # Start-Ups X Env. Scanning Squared			**0**
			[0.000]
Prior # Apps Developed	**0.084*****	**0.095*****	**0.094*****
	[0.009]	[0.009]	[0.009]
Education	**-0.025**	**0.008**	**0.003**
	[0.025]	[0.026]	[0.027]
Managerial Experience	**0.031*****	**0.030*****	**0.035*****
	[0.005]	[0.006]	[0.006]
Innovation Measure	**-5.556*****	**-4.015*****	**-4.240*****
	[1.159]	[1.164]	[1.190]
Financing Amount	**0.000*****	**0.000*****	**0.000*****
	[0.000]	[0.000]	[0.000]
Paid	**-2.447*****	**-2.596*****	**-2.529*****
	[0.119]	[0.122]	[0.128]
Offer In App Purchases	**1.020*****	**0.716*****	**0.735*****
	[0.078]	[0.082]	[0.082]
Purpose	**0.671*****	**0.522*****	**0.544*****
	[0.070]	[0.073]	[0.074]
Full Time	**0.118+**	**0.110+**	**0.094**
	[0.060]	[0.064]	[0.065]
Time on Market (days)	**-0.011*****	**-0.010*****	**-0.010*****
	[0.001]	[0.001]	[0.001]
Games Category	**-0.05**	**-0.086**	**-0.044**
	[0.058]	[0.060]	[0.060]
Country=USA	**-1.921*****	**-1.800*****	**-1.823*****
	[0.067]	[0.068]	[0.069]
Wave Fixed Effects	**Included**	**Included**	**Included**
Observations	5,820	5,820	5,820
Log Likelihood	-5484	-5422	-5395
Pseudo R-Squared	0.219	0.228	0.231

Robust standard errors in brackets
**** p<0.001, ** p<0.01, * p<0.05, + p<0.1*

Table 4.4

Ordered Logit Models for Install Category, Additional Tests

VARIABLES	**Model 1**	**Model 2**
Prototypes Tested	**0.008**	**0.009**
	[0.025]	[0.006]
Environmental Scanning Time	**0.011*****	**0.008*****
	[0.003]	[0.002]
Env. Scanning Time Squared	**-0.000*****	**-0.000*****
	[0.000]	[0.000]
Prior # Start-Ups	**-0.082*****	**-0.057**
	[0.022]	[0.068]
Prior # Start-Ups X Prototypes	**0.006**	**0.030*****
	[0.004]	[0.005]
Prior # Start-Ups X Env. Scanning	**-0.004*****	**0.003****
	[0.001]	[0.001]
Prior # Start-Ups X Env. Scanning Squared	**-0.000*****	**0**
	[0.000]	[0.000]
Env. Scanning X Prototypes	**0.002***	**0**
	[0.001]	[0.000]
Controls	*Included*	*Included*
Wave Fixed Effects	*Included*	*Included*
Observations	4,112	5,820
Log Likelihood	-4217	-5395
Pseudo R-Squared	0.175	0.231

Robust standard errors in brackets
**** p<0.001, ** p<0.01, * p<0.05, + p<0.1*

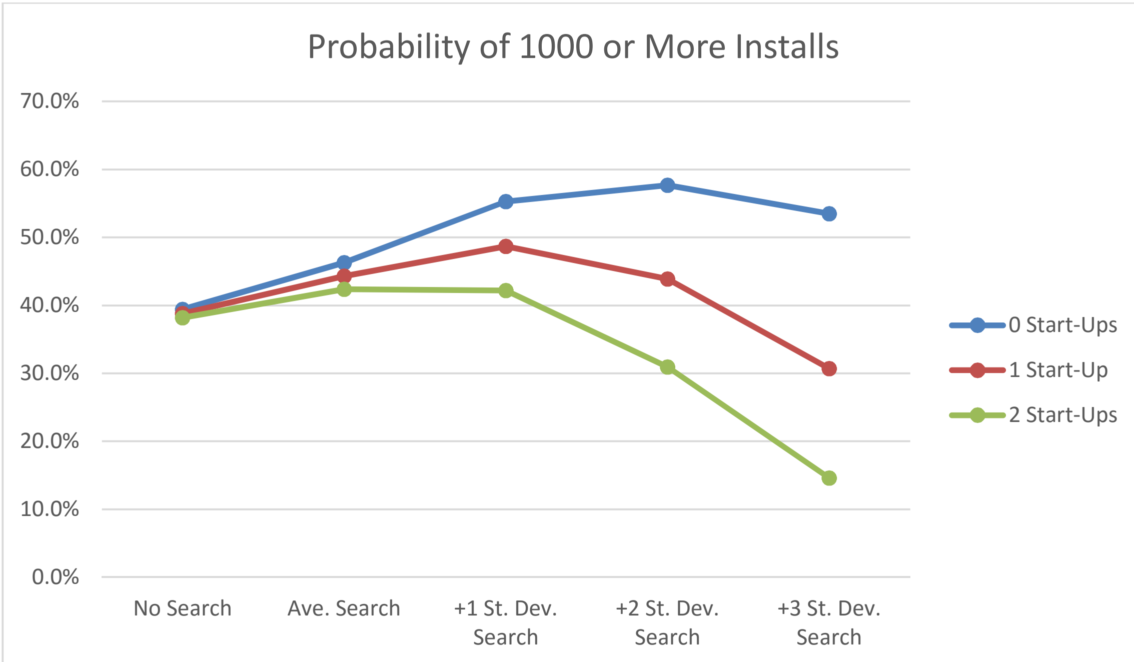

Figure 4.1: Novice and Experienced Entrepreneurs Versus Environmental Scanning

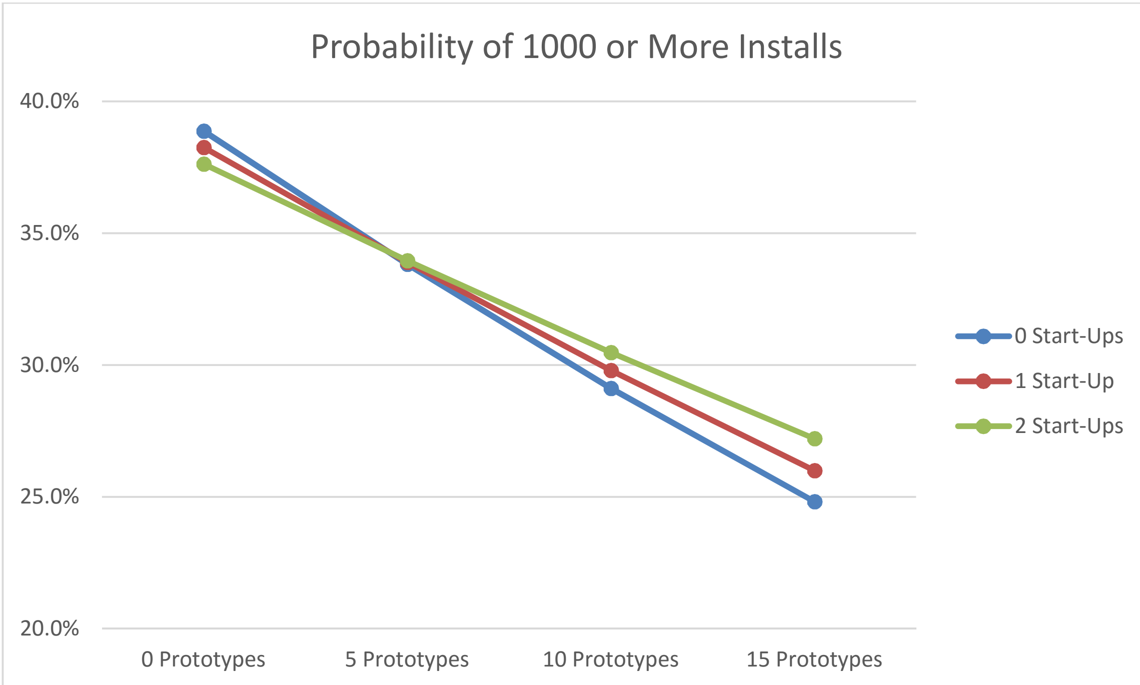

Figure 4.2: Novice and Experienced Entrepreneurs Versus Prototype Testing

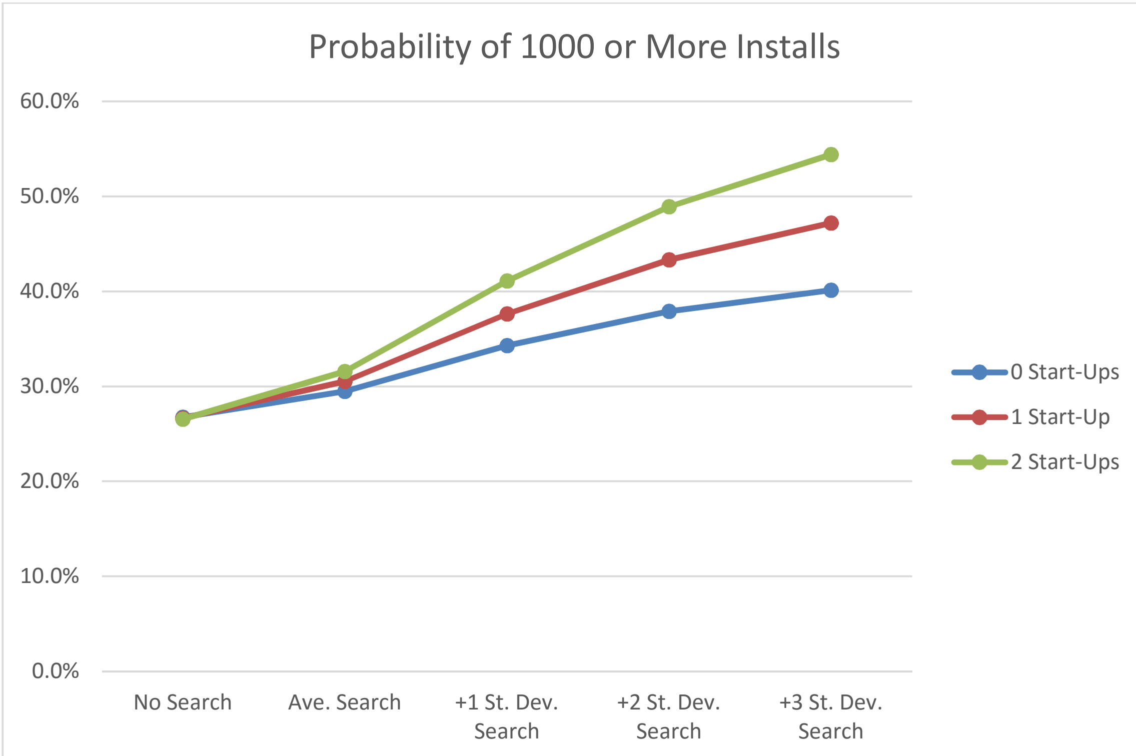

Figure 4.3: Novice and Experienced Entrepreneurs Versus Environmental Scanning

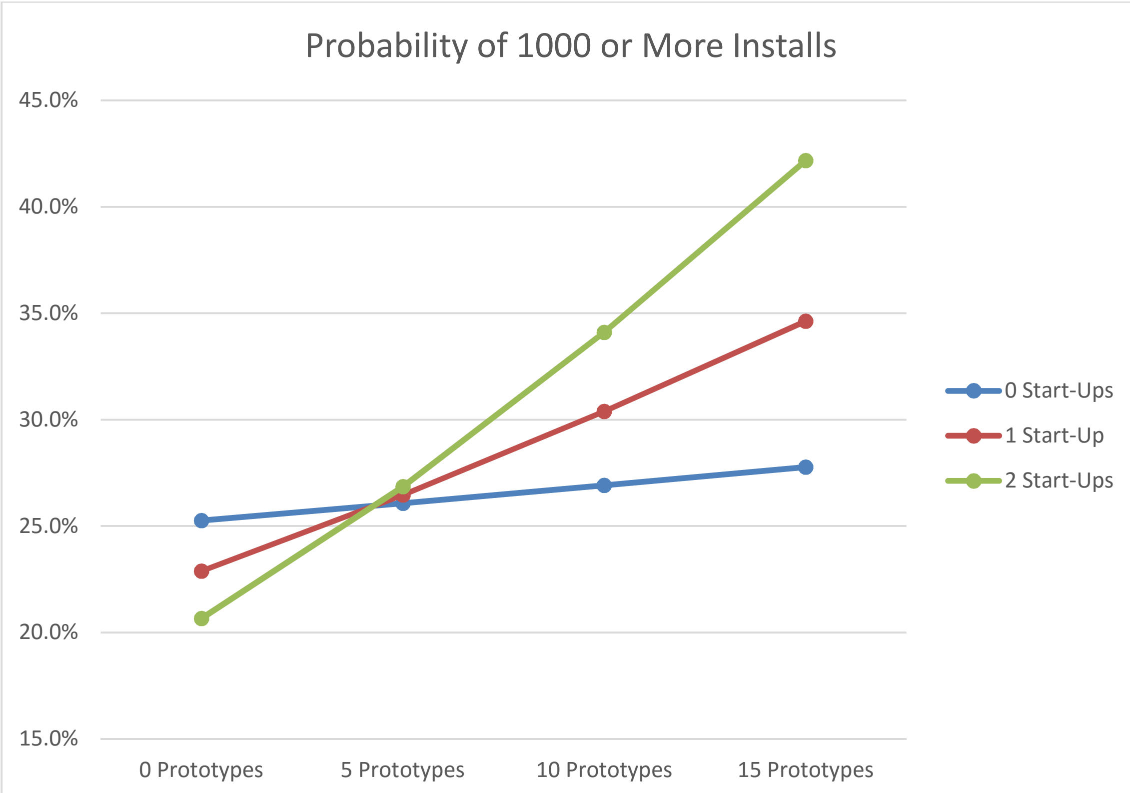

Figure 4.4: Novice and Experienced Entrepreneurs Versus Prototype Testing

CHAPTER 5

CONCLUSION

Management researchers are becoming increasingly interested in the role that individuals play in the performance of organizations. This dissertation examines several different aspects of the relationship between individuals and organizations, across two distinct contexts. The first paper examines the mobility of star employees in the National Football League. The second and third papers examine mobile application developers, and how their prior experience impacts the performance of their applications.

In the first study of this dissertation, the research shows that adding stars can improve an organization's performance, even in a situation where moderate levels of team coordination are needed. This is despite the fact that the individual star does not, on average, perform as well with their new team. The results suggest that by adding a star, an organization can improve the performance of their other employees. This research suggests that it is better to keep your current stars and add new ones to improve your organization's performance.

In the second chapter, this research showed that an entrepreneur's human capital investments are not independent, and in fact, the performance effects of investments depend on the level of other investments. We find that some of an entrepreneur's general human capital investments improve the performance implications of their industry-specific task and prior start-up experience, while other types of investments reduce the value of specific investments. We also find that higher levels of both education and managerial experience lead to higher performance. Finally, we find that high levels of both industry-specific task experience and prior start-up experience lead to lower entrepreneurial performance. When examining human capital investments, both researchers, manager, and entrepreneurs should remember that these investments are not independent, but impact each other.

In the final chapter, this research found that for novice entrepreneurs exploiting less novel opportunities, environmental scanning improves performance (up to some threshold), while prototype testing actually reduces performance. For experienced entrepreneurs, this research found that scanning the environment also improves performance, but the peak amount of scanning is lower for these entrepreneurs, and performance falls off more quickly after the peak. This research finds that prototype testing is not effective for more experienced entrepreneurs exploiting less novel, more imitative apps. For more novel opportunities, this research found that novice entrepreneurs do not improve performance by prototype testing, but more time spent scanning the environment does increase performance. For more experienced entrepreneurs exploiting more innovative opportunities under uncertain conditions, this research found that environmental scanning improves performance more than it does for novices, but also at a diminishing rate. Finally, this research found that prototype testing is extremely effective for experienced entrepreneurs exploiting more novel opportunities. Overall, our results point to the further differences between novice and experienced entrepreneurs, and that the actions taken by each have different performance implications for different types of opportunities.

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